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Three Essays in Empirical Industrial Organization

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Three Essays in Empirical Industrial Organization

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I dedicate this dissertation to my family. To my parents Margaret and Allan for providing strong support from the beginning and never losing the faith in me. To my brother Aaron for helping me keep things down-to-earth and in perspective, and to my brother Nathan who, through all our long conversations, has been particularly understanding since he is also completing his dissertation.

I would also like to dedicate this dissertation to Ed Whitelaw for spurring my interest in economics and getting me started.

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Three Essays in Empirical Industrial Organization

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There are many differentiated product industries in which firms offer multiple products in the same market. In making strategic decisions regarding entry, quality and quantity to be supplied for their multiple products firms must consider the competition with rivals as well as cannibalization of their own products that are close substitutes. In this setting, understanding the relationship between the behavior of consumer demand and firms decisions' regarding product characteristics and strategic variables like advertising are fundamental issues in industrial organization. This dissertation empirically explores these fundamental issues in the pharmaceutical and airline industries.

The first paper of my dissertation estimates consumer demand for different

anti-cholesterol drugs using panel data on a nationally representative sample of individuals who were diagnosed with cholesterol problems in the period 1996-2002. The data provides detailed information on individuals' medical conditions, medical and drug insurance coverage, drug purchases (if any), and other demographic and medical information. Individuals choose whether to purchase an anti-cholesterol drug and, if so, which drug to buy. The model permits flexible substitution patterns among drug choices and persistence in those choices by incorporating both observed and unobserved consumer heterogeneity. The estimates suggest that lower income patients without prescription drug insurance are very price sensitive: they are less likely to use drugs and, if they do use them, they tend to purchase the less expensive drugs. I find that roughly 500 thousand individuals without drug insurance who are currently not purchasing anti-cholesterol drugs would do so in the counterfactual world in which they are given the standard co-payment plan.

The second paper also looks at consumer demands for anti-cholesterol drugs. While the first paper focused on the differentiated products, this paper explores the market expansion effects of direct-to-consumer advertising (DTCA). The study combines the individual data used in the first paper with monthly expenditure data on DTCA for the period 1996-2002. The dynamic demand model estimated in this paper explores the heterogeneous effects of DTCA. Overall, I find a positive effect from DTCA with short term elasticity of 0.107. Through persistence in consumer demand this effect lasts over multiple time periods. I find that individuals not taking a cholesterol drug respond more to advertising than those on the drug. In addition, I find that less educated individuals, those that may be unaware of their health condition, and those without health insurance are most responsive to DTCA.

Finally, the third paper studies the effect of product ownership and quality on entry in the airline industry. Specifically, this paper empirically examines the decision of an airline to offer high quality nonstop service between cities given that

the airline may or may not be offering lower quality one-stop service. I find that airlines that offer one-stop service through a hub are less likely to enter that same market with nonstop service than those that do not. In addition, the quality of the one-stop service is another determinant of entry. Airlines are more likely to enter a market with nonstop service if their own or their rival's one-stop service in the market are of lower quality.

Contents

Chapter 1

The Impact of Prescription Drug Insurance on the Demand for Anti-Cholesterol Drugs

1.1 Introduction

According to Eric Topol (2004), an estimated 36 million people in the United States should be taking cholesterol reducing drugs from the statin class. However, only 11 million are currently being treated.[1] Furthermore, half of the people that begin statin drug therapy stop after six months, and only 30-40% are still taking their medication after one year.[2] These statistics suggest a serious public health problem because high cholesterol is a primary risk factor in developing heart disease, the leading cause of death in the United States. One explanation for the underuse of

[1] Topel (2004) provides this statistic. His estimates are based on current national guidelines for taking cholesterol drugs and population estimates from Ford et al (2003).

[2] These statistics are especially disturbing because it takes 6 months to 1 year for the benefits from the treatment to become perceptible. This information is from Third Report of the National Choelesterol Education Program: Adult Treatment Panel III (NCEP (2001)). This report is produced by a panel of doctors that summarize the most recent medical findings and provides recommendations for the testing and management of high cholesterol and a number of other subjects.

statin drugs is that they are expensive: the price of a years supply of a drug is over $700. The goal of this paper is to estimate the demand for statin drugs and determine how much of the "underuse" of statin drugs can be explained by high drug prices and the lack of full prescription drug insurance coverage.

My data consists of panel data on a nationally representative sample of consumers who were diagnosed with cholesterol problems in the period 1996-2002. The data is from the Medical Expenditure Panel Survey (MEPS), which provides detailed information on the consumers' medical conditions, medical and drug insurance coverage, drug purchases (if any), and other demographic and medical information. The vast majority of individuals in the sample have medical insurance but only two-thirds have drug insurance. The typical insurance plan involves a co-payment, and covers roughly 65% of the patient's drug costs.

Doctors are assumed to inform their patients about possible drug treatments. Patients then choose whether to use an anti-cholesterol drug and, if so, which drug to buy. I model their choices using a discrete-choice, mixed logit model with observed and unobserved product and consumer heterogeneity. The model permits flexible substitution patterns among the choices and persistence in those choices.[3] It is particularly well-suited for modeling the demand for drugs since the effectiveness of drugs and their side-effects are idiosyncratic. The model is estimated using simulated maximum likelihood.

The main empirical finding is that patients without prescription drug insurance, particularly low income patients, are quite sensitive to price. I use the demand estimates to calculate the consumer benefits of different drugs such as Lipitor, which entered the market in 1997, and generic brands, which have entered the market re-

[3] The importance of persistence in prescription drug choice by doctors and consumers is a well established in the literature. Hellerstein (1998) shows persistence in doctor prescribing patterns between generic and brand name drugs in the U.S., Coselli (2004) finds that consumers exhibit strong state dependence, and Richard and Van Horn (2004) find persistence in demand because many prescription drug purchases may be classified as automatic renewals.

cently. I also perform a number of policy experiments. When patients with no prescription drug insurance are given the standard co-payment plan, their demand for statin drugs increases by 9%, or roughly 500,000 individuals switch from not using statin drugs to using them. In an out-of-sample counterfactual experiment where all individuals have full insurance, demand for statin drugs increases by 35%, with approximately 5 million individuals becoming users.

The paper contributes to the recent empirical work that models the market for drugs as a differentiated market and estimates drug demands using discrete choice models. Cleanthous (2002) estimates demands for drugs in the antidepressant market using market share data, augmented with micro level data containing information on the joint distribution of income and insurance coverage in the population. He adopts the approach pioneered by Berry, Levinsohn, and Pakes (1995). His objective is similar to mine, namely, to estimate the impact of prescription drug insurance and income on demands, and the welfare benefits from new drugs. The main difference between our studies is that I am able to match the individuals income, insurance coverage, and detailed condition information with their drug choice. A number of papers have shown that this type of information is important to obtaining more realistic demand estimates.[4] This issue may be especially important in health markets where insurance coverage and disease are both heterogeneous and correlated (e.g. cholesterol increases with age and Medicare covers most people over the age of 65).[5]

Wosinska (2002) also studies the market for statin drugs using panel data on individual drug choices. Her econometric model of consumer demand is similar to the one that I use. Key differences are that she includes the individual's past

[4] e.g. Goldberg (1995), Petrin (2002) , and Berry, Levinsohn, and Pakes (2003).

[5] A number of other papers have also estimated market demand for prescription drugs using market share data including Ellison et al (1997) examining anti-ulcer drugs and applying a budget share approach, Stern (1996) looking across multiple drug classes and applying a nested logit model, among others (e.g. Rizzo (1999) and Berndt et al (1995))

choice in the econometric model and the choice set in her model does not include the choice of no drug. The reason she excludes the choice of no drug is that her data consists of a sample of purchasing records from privately insured individuals. Hence, she can estimate how individuals respond to price changes within the market but she cannot estimate the market expansion effects of price changes or changes in insurance. Her focus is primarily on the impact of direct-to-consumer advertising on consumer choices of prescription drugs.[6]

This paper is organized as follows: The next section provides some background on the market for statin drugs. Section 3 describes the econometric model. Section 4 discusses the data followed by section 5 with a discussion of the results. Section 6 looks at welfare effects and section 7 presents results from policy experiments. The last section concludes.

1.2 The Market for Statln Drugs

Statin drugs have been the top selling class of drugs in the U.S. during the period between 1999 to the present with total revenues of $12.5 billion dollars in 2002. Statin drugs are relatively new, with the first drug, Mevacor, introduced in 1987. Several drugs have entered the statin class since then including Pravachol, Zocor, Lescol, Lipitor, and Baycol.[7] In 2002, Lipitor and Zocor were the highest selling drugs in the world.[8] Each of these drugs was patented with a unique molecule and, for most of the sample these patents were enforceable. As a result, generic firms could not enter the market, and prices were relatively high. The typical cost per day was about $2.[9] Revenues to the statin class of drugs were also high because

[6] Some other studies using micro level data to analyze market demand include Donohue and Berndt (2004) using claims data and Iizuka and Jin (2005) using National Ambulatory Medical Care data.

[7] Several other drugs have entered the class since the end of my sample in 2002.

[8] From IMS health pharmaceutical sales estimates.

[9] Generic manufacturers can legally offer new products in a market using the active molecule of a drug when the drugs patent expires.

of the prevalence of cholesterol problems and the effectiveness of these drugs at treating high cholesterol. According to estimates from the Center for Disease Control and Prevention, 17 % of individuals over 20 have high cholesterol.[10] For many patients, the consequence of not taking cholesterol reducing drugs is detrimental to their health. The world health organization estimates that high-cholesterol is a contributing factor to 4.4 million deaths in the world each year. It is a contributing factor in 56 % of clinical heart disease cases and 18 % of strokes.[11] According to the national treatment guidelines reported in NCEP (2001), the primary goal of drug therapy for patients with high cholesterol is to attain lower LDL cholesterol levels. Evidence from epidemiological studies suggest that lower levels of LDL cholesterol (bad cholesterol) are associated with lower overall risk of clinical heart disease morbidity and mortality. The statin drugs are the most effective at lowering LDL cholesterol, have few side-effects, and are easy to administer.[12]

Statins are typically the first drugs prescribed for the treatment of high cholesterol. They are an important part of the prevention of heart disease, stroke, atherosclerosis and other atherosclerotic conditions. Atherosclerotic conditions include any condition related to the deposition of cholesterol that builds up as plaque on the innermost layer of the walls of large and medium-sized arteries. The active molecules in the statin class work by controlling the key enzyme that controls cholesterol in the body. The effect of statin drugs is that they lower LDL cholesterol (bad cholesterol) and triglycerides levels (also bad), and increase HDL levels (good cholesterol).

Statin drugs offer significant advancements over preexisting drug treatments.

[10 0] The statistic is reported in Health, United States (2005). High cholesterol is defined as serum cholesterol levels of 240 or higher. This statistic is a projection of the number of individuals that have high cholesterol, so the number that actually know that they have a cholesterol problem is less.

[11 1] World Health Report (2002)

[12 2] One side effect may be myopathy accompanied with muscle aches, but the incidence of this occurring is low.

There are three other classes of drugs that may be used to treat high cholesterol. The second most effective class for lowering LDL cholesterol are bile-acid sequestrants. In addition to being less effective at reducing LDL levels, bile acid sequestrants are used less often than statins because of a variety of gastrointestinel side-effects among other problems . The other two classes of drugs, fibric acid derivatives and niacin, are the least effective at lowering LDL cholesterol, and they are primarily used for treating other aspects of cholesterol. Fibric acid derivatives are typically used to treat high triglyciride levels, and niacin is effective at treating low HDL cholesterol. One might consider these other classes of drugs to be substitutes for the statin class, but they are often used in combination with statin drugs. The differences between the drug classes, and the possibility that they may be used in combination with statins, are the main reasons for excluding them from the current analysis.

Although statin drugs have similar effects on the different components of cholesterol, the effectiveness of the drugs within the class varies. Table 1.1 lists some of the basic characteristics of the statin drugs. The last two columns of Table 1 indicate that Lipitor is relatively more effective at lowering LDL cholesterol at both the typical dose and high dose relative to the other drugs. This is important because cholesterol goals are more likely to be reached if a more effective drug is used. Also, side effects are typically lower for lower doses of a drug.[13]

Statin drugs also vary in their effectiveness in treating different types of conditions. Table 1.2 reports the various conditions that the different statin drugs are indicated to treat. The information is drawn from the Clinical Pharmacology (2005) database.[14] The conditions are listed in the first column. The first three are primary treatments used to prevent a condition, and the last four are secondary

[13 3] It has been shown that increasing dosage levels of a drug also increases the occurrence of side effects. However, according to NCEP (2001) it is not clear how a low dose of one drug such as Lipitor compares to a high dose of a less effective drug such as Lescol.

[14 4] The Clincical Pharmacology database provides peer reviewed, clinically-relevant information on drugs available in the United States. The information includes off-label uses.

treatments used to stop or reverse an existing condition. The treatment of cholesterol is an example of primary treatment because lower cholesterol prevents heart disease and other diseases related to hardening of the arteries. All six drugs are indicated to treat each of the cholesterol disorders, with the exception of Mevacor, which is not indicated to treat high triglyciride levels. The treatment of atherosclerotic conditions is an example of secondary prevention because the goal is to stop or reverse the disease. The usefullness of the drugs in treating these conditions vary more widely than in the case of cholesterol disorders. Pravachol is indicated to treat all atherosclerotic conditions, whereas Baycol is not indicated to treat any of them.

Even though certain statin drugs are more effective at lowering cholesterol, one brand is not necessarily the best drug for all people. For instance, if the goal of an individual is to lower her LDL cholersterol by only 20%, then all drugs are reasonable alternatives. Also, the effectiveness of drugs and their side effects are likely to be somewhat idiosyncratic.

Table 1.3 documents the set of available drugs for each year in the sample period and their market shares in our sample. The most dramatic change in the market was the entry of Lipitor in 1997. Lipitor had over 15% of the market in its first year, and nearly half of the market by the end of 2002. By contrast, Baycol, which entered in 1998, had only 2% market share in its debut year. Its market share stayed small before it voluntarily withdrew in August of 2001 because it was linked to over 31 deaths caused by muscle cell damage. Although Baycol was relatively inexpensive, it did not offer any significant advantages over the drugs already in the market. Mevacor lost patent protection on December 17th of 2001. On the same day, several generic firms were approved by the FDA to produce drugs using Lovastatin, the active molecule in Mevacor. The generic versions of Mevacor captured approximately 5% of the statin market in their first year of entry.

1.3 Econometrlc Model

In contrast to most consumer purchasing decisions, in prescription drug markets, consumers rely on their doctors to tell them which drug, if any, is best suited to treat their condition. The doctors inform their patients based on their knowledge about the clinical properties of the drugs from the medical literature, the treatment history of their patients, information from fellow doctors and advertisers, as well as their own personal experience in prescribing the medicine. I assume that doctors truthfully inform their patients about possible drug treatments and their effectiveness, and that patients then choose whether to use an anti-cholesterol drug and, if so, which drug to buy. In other words, I ignore any agency problems between doctors and their patients, and assume that patients are able to make an informed treatment decision.

In each period, consumers choose a treatment that maximizes their utility. The set of treatment options is $\{0, ..., J_t\}$ where $J_t + 1$ is the number of treatment options available in period t. Here the option 0 is the choice not to take a drug. The consumer only chooses one type of treatment. Given the information from the doctor, consumer i chooses option j E $\{0, ..., J_t + 1\}$ in period t if

$$u_{ijt} > u_{ikt} \quad \text{'Ilk} / \quad j$$

I assume that consumer i's indirect utility for drug j, j / 0, at time t is given by

$$u_{ijt} \quad a_{it}p_{jt} + j3_{it}x_{jt} + T_{ij} + E_{ijt},$$

where p_{jt} is the price of drug j in period t, x_{jt} is the vector of characteristics of drug j in period t, T_{ij} is consumer specific taste parameter for drug j that does not vary over time, and E_{ijt} is the idiosyncratic component of a consumer's utility for drug j that varies over time. The mean utility of the no drug option is normalized

to be zero. The response of consumer i to price and drug characteristics consists of a component that is common to all consumers and a component that depends upon her observed characteristics, z_{it}, such as drug insurance coverage and health condition:

$$a_{it} \quad a_O + a_1 z_{it}$$

and

$$j3_{it} \quad j3_O + j3_1 z_{it}.$$

The consumer-specific unobservables that do not vary over time enter the model using an error component framework. I allow T_{ij} to be correlated for j / 0, but assume that T_{iO} is independent. This allows drug options to be closer substitutes than the no drug option. Similarly, I allow for unobserved correlation between the branded version of Mevacor and it's generic counterpart. More precisely, I assume that $T_{ij} \quad F r(_i$ where F is a fixed matrix of size J_t x M where each cell is either 0 or

1. Although F ,r and $(_i$ change as the choice set changes. The vector $(_i$ is a vector of i.i.d. normal random variables with unit variance. The matrix r is an M x M diagonal matrix of unknown parameters to be estimated. The error component framework can produce flexible correlation patterns over choices. In addition, it is fairly easy to introduce various correlations structures between choices. For instance, I can introduce drug specific heterogeneity in utility by including a single 1 in the column of F with the rest of the values in that column equal to zero. That value is multiplied by a parameter in r that corresponds to the standard deviation in utility for a specific drug. Including a column vector of all 1's in F except for the no-drug option allows for correlation among the drug choices. The covariance matrix for T_i is $'L_{,t} \quad F rr^t F^t$. The first section of the appendix includes a more detailed discussion of the specification and covariance matrix used in this paper.

The unobserved idiosyncratic component of the consumer's utility function,

E_{ijt} , is assumed to be distributed i.i.d. extreme-value so that, conditional on observing the vector T_i, the probability of choosing option j takes the logit form:

$$\text{Prob}_{it}(j, T) \quad \frac{\exp(a_{it}p_{jt} + j3_{it}x_{jt} + T_{ij})}{'I_{,k=O}^{J}\exp(a_{it}p_{kt} + j3_{it}x_{kt} + T_{ik})}$$

I observe T_i distinct decisions for individual i . Let this sequence of choices be denoted ȷ̇ $\{j_l, ..., j_{T_i}\}$, so the probability of observing this sequence conditional on T_i is:

$$e_i(\dot{j}, T_i) \quad \prod_{t=O}^{T_i} \frac{\exp(a_i p_{jt} + j3_i x_{jt} + T_{ij_t})}{'L_{,k=l}^{J_t}\exp(a_i p_{kt} + j3_i x_{kt} + T_{ik})}$$

Since T_i is not observed, it is necessary to integrate over the multivariate distribution $\mathbf{j}(T\,I'L,)$ to obtain the unconditional probability of observing the sequence of choices ȷ̇. The parameter matrix 'L, is the variance-covariance matrix of the consumer-specific errors. The unconditional probability of the sequence of choices ȷ̇ is:

$$e_i(\dot{j}) \quad \int_{r} \int_{r} \prod_{t=O}^{T_i} \frac{\exp(a_i p_{j_t t} + j3_i x_{j_t t} + T_{ij_t})}{'L_{,k=l}^{J_t}\exp(a_i p_{kt} + j3_i x_{kt} + T_{ik})} \mathbf{j}(T\,I'L,)dT$$

The log-likelihood function is then:

$$\sum_i \log(e_i(\dot{j}))$$

The above integral does not have a closed form solution, so I employ simulation to integrate over the distribution of T . Simulation is done by first taking R vectors of simulation draws from the distribution $\mathbf{j}(T\,I'L,)$ for each consumer. The rth vector of simulation draws T_i^r is taken from a standard normal distribution with unit variance and stacking these random draws in the vector ($_i^r$ and calculating T_i^r $Fr(_i^r$. For each T_i^r the probability a consumer makes the sequence of choices ȷ̇ is evaluated, then I average the probabilities to obtain the predicted probability

that the consumer makes this sequence of decisions:

$$e_i(\dot{\jmath}) \quad \frac{1}{R} \sum_{r=1,\ldots,R} e_{ij}(\dot{\jmath}, T^r)$$

The simulated log-likelihood function is then $\sum_i \log(e_i(\dot{\jmath}))$. I search for the parameter values, $\{a_O, j3_O, a_l, j3_l, r\}$, that minimize the simulated log-likelihood. The same simulation draws are used by the same consumers throughout the maximization procedure.[15]

Making sure that all the parameters in the model are identified can be tricky. Issues related to identification in mixed logit models are discussed in detail in Ben-Akiva at al (2001). To identify all the parameters of the model, I find that it is necessary to normalize certain parameters so that the model can be identified. One normalization of the model was made already by setting the variance of E_{ijt} to $w^2/6$ which gives the logit probability above. Another normalization that is applied is to set the random error on the no drug treatment option to be equal to $N(0, 1)$. The details involved in checking whether the model is theoretically identified is covered in the second section of the appendix.

This paper uses maximum simulated likelihood to estimate the above model. One problem associated with maximum simulated likelihood is that bias arises for a finite number of simulation draws.[16] There are a number of approaches for dealing with this bias. A brute force approach is to simply take a large number of random draws, but this is computationally taxing. In this paper I employ Halton sequences of random draws. Halton sequences are carefully selected psuedo-random draws that provide greater coverage with a fewer number of draws. This reduces bias and makes the estimation of the relevant integral more precise. Train (2003) shows

[15] I do not apply individual weights during the estimation procedure, but population weights are used after the procedure in making predictions for the entire population.

[16] Let f^s be the likelihood as calculated using simulation draws. Because of Jensen's inequality $E\log(f^s) < \log(Ef^s)$ so there is bias in the procedure unless f^s is very close to f.

that 100 random draws from a Halton sequence performs as well, if not better, than 1000 random draws using the standard approach. The simulation procedure for my model uses 200 Halton sequence random draws.[17] The standard errors of this model are computed in the usual way.[18]

The above model assumes that the consumer maximizes utility in each period. Persistence in consumer choices is captured through observable factors such as health conditions and the consumer-specific, unobservable factor that does not vary over time. I could attempt to separately identify state dependence and consumer specific heterogeneity by included the previous treatment choice of the consumer in the above model. This is the approach taken by Wosinska (2002). However, because the first choice of the consumer is not observed, including a variable indicating the consumers previous choice introduces an initial conditions problem. This problem arises if the random consumer-specific error is correlated with the initial treatment choice. An example of an unobserved consumer specific characteristic that might induce this type of correlation is the consumers unobserved LDL level for his first cholesterol check.

A key identifying assumption of the model is that prices are uncorrelated with the consumer-specific unobservables. This assumption is commonly made in studies that use consumer level data (e.g., Goldberg (1995) and Shum (2004)). Villas-Boas and Winer (1999) is the one demand study that I am aware of that tries to account for price endogeneity. The problem arises from unobserved drug characteristics that affect every consumer's utility from the drug. Drug companies will tend to charge higher or lower prices depending upon whether the unobserved drug characteristics

[17] [7] Although using Halton sequences significantly reduce the number of random draws needed to obtain unbiased estimates, the actual number of draws necessary to obtain precise estimates depends on the particular application.

[18] [8] In calculating the standard errors I assume that the model specified is the true model, and then I appeal to the asymptotic properties of the maximum likelihood estimation to obtain the asymptotic standard errors. After completing the estimation procedure, the numerical hessian of the model is calculated. After obtaining the hessian I then multiply the hessian by negative one and take its inverse. The standard errors are the square-root of the diagonal of the derived matrix.

have a positive or negative impact on demand. As a result, the consumer-specific unobservables will be correlated with prices. To address this issue, I include product dummy variables, which account for unobservable drug characteristics that are invariant over time. However, unobserved drug characteristics that vary over time and are correlated with price changes remains a problem. For example, any changes in consumers' perceptions about the relative effectiveness of the drugs due to new information or advertising are likely to be correlated with price changes. Additional analysis will be needed to determine the importance of this assumption.

1.4 Data

The main data source used in this paper is the Medical Expenditure Panel Survey (MEPS) from 1996-2002. The survey contains extensive information on medical care in the United States, and it is used to provide national estimates on health care use, medical expenditures, and insurance coverage for the U.S. civilian, noninstitutionalized population. The MEPS selects a random sample of households and surveys all individuals in a household. It follows the individuals for two years, during which it records information on individuals in 5 rounds, where each round is approximately 4-6 months. The data recorded in each round includes details on the individual's insurance, demographic characteristics, health condition, and medical expenditures. In the analysis that follows, I will define a period as a round. The MEPS study supplements the survey data by contacting the individual's medical providers and pharmacies to obtain billing information. For instance, if a patient reports purchasing Zocor from a specific pharmacy, the pharmacy is contacted to provide a payment history for all purchases of Zocor from the individual. Each year approximately 15,000 individuals enter the data so the data set is an overlapping panel.

The survey reports whether individuals have medical and/or prescription

drug insurance and the type of plans. If the insurance plan is public, then the data identifies the provider, that is, whether it is Medicare, Medicaid, or some other public agency. Medicare provides medical insurance but no prescription drug insurance, whereas Medicaid provides both. The data on private plans includes whether the plan covers doctors visits, prescription drugs, and/or other services. Additional information about the individual's insurance coverage can be inferred from the individual's medical expenditures. Each time a consumer visits a doctor or purchases medical services such as prescription drugs, the survey records the amount charged and who pays, whether the payment is paid directly by the consumer or paid by a third party. The third party payments are classified as private, Medicare, Medicaid or various other types of public insurances. Unfortunately, the MEPS data does not provide detailed information on the structure of the individual's drug insurance plan.[19] The MEPS only contains information on payments for drugs purchased by an individual, and not on drugs that she does not purchase. For example, if an individual purchases Zocor, we observe her out-of-pocket cost for Zocor, but not for other statin drugs that she could have purchased.

Individuals are asked to write about their current medical condition and health history, including when their medical problems began. For each medical event (e.g., doctor visit or prescription drug purchase), individuals are asked about the medical conditions that gave rise to the event. Professional coders take the information provided by the individual and assign one of 5 digit ICD-9 codes (International Classification of Disease Code, Ninth Revision) which describe the individual's medical condition. To protect the identity of individuals in the sample, the 5 digit ICD-9 code is aggregated into 3 digit ICD-9 codes. The 5 digit ICD-9 codes are also aggregated into 260 clinically meaningfully categories using Clinical Classification Software. In this paper, both the 3 digit ICD-9 codes and clincial

[19] [9] There is a wide variety of features that an insurance plan might have such as formulary restric- tions, deductibles, and copayments that may be fixed or vary across drugs.

classification codes are used to describe the individuals medical condition. After reviewing risk factors mentioned in the NCEP (2001) report, and with the help of Dr. Rasmussen, I classified the 3 digit ICD-9 and clinical classification codes into the four categories: cholesterol disorders, atherosclerotic conditions, diabetes and hypertension. The classification is described in Table 1.4. The only group requiring more than one code was atherosclerotic conditions. This grouping consists of various forms of heart disease, atherosclerosis, stroke or prior heart attacks. All of the problems listed above are chronic conditions, so that once an individual is observed as having the condition, he is assumed to continue to have the condition.

The prescription drug transaction data provided in the MEPS includes the quantity, the strength, and the National Drug Code (NDC) of each drug purchased. The NDC code is a number that uniquely identifies a drug and can be used to link the drug to the manufacturer and a specific product. Conversion from the NDC code to a specific product is done using online data available from the FDA website that links NDC codes to the products and manufacturer. In cases where the NDC code of the drug is not listed, I used the name of the drug's active molecule as listed by the pharmacist, and whether the drug is branded or generic to determine the identity of the statin drug.[20] Recall that, for most of the sample period, the drugs in the statin class are branded and have a unique molecule.[21]

The data on visits to medical providers include visits to the doctors office, inpatient and outpatient hospital visits, and emergency room visits. Detailed in-

[20] The MEPS data center uses a proprietary database to impute the NDC code for their internal use, but this is not publicly available.

[21] In a few cases, I was not able to identify the drug. At the end of 2001 the drug Mevacor goes off patent. At this time a number of generics enter the market that also use Mevacor's active molecule called Lovastatin. I group the drugs sharing the Lovastatin molecule into two categories, branded and generic. Another case where a unique drug cannot be assigned to a round is when multiple Statin drugs are purchased. Since multiple Statin drugs are typically not prescribed, it is likely that a patient has switched drugs. So in cases where two drugs are purchased in a round, I assign the last drug taken in the round. I use information on the drug taken in the previous or following round to determine the drug that a person is switching to. If that information is not available I assign the drug with the greatest quantity purchased in the round.

formation on each visit is recorded including information on the date of the visit, expenditures on the visit, and the condition related to the visit. These data are used to determine whether and when consumers are informed about their medical conditions and possible treatments.

I performed two checks on the MEPS data to determine whether the sample is representative. I compared its estimate of the number of uninsured to that reported in the Census for 2002 and found that they matched. The Census estimate of the number of uninsured is 45.8 million, while the number from the MEPS is 43.6 million. I also computed the annual estimated national revenue shares in the MEPS of the top three sellers - Lipitor, Pravachol and Zocor - and compared them to the those reported in IMS health. IMS health is a pharmaceutical market research firm that monitors drug sales from pharmacies. It reports total revenue data for the statin class and for each of the three top sellers for the years 1999-2002.[22] Table 1.5 reports the IMS and MEPS revenues shares for the three drugs for each year during the period 1999-2002. The differences are relatively small, differing by at most 3.22% in any one year. I conclude that the MEPS sample provides a good approximation to the market.

1.4.1 Variables

The dependent variable used in this paper is the treatment choice in a round. The treatment choices include the statin drugs that are available in the market during the round and the no-drug treament option. As stated previously, I assume that if the individual takes any drug in a round, then she is considered to be using drugs in that round.

In determining the size of the market, I apply two rules. First, I limit the set of potential buyers to those with either a cholesterol disorder or an atherosclerotic

[22] [2] I would have liked to have a more detailed comparison, but unfortunately this data was too expensive.

condition. Second, a person must be informed to be included in the sample. I define a consumer as informed in a round if he has visited a doctor or taken a drug in the current or previous round. Although a consumer may know he has a condition, if he does not visit a doctor, he may not be aware of the treatment options available. I drop the first round for each individual in the sample in order to account for potential stockpiling of drugs used in subsequent rounds. To account for stockpiling, I assume that the average daily dose for each drug is taken, and I divide the total quantity of dosages purchased by the average daily dose to determine the number of treatment days purchased. If the number of doses exceed the number of days in a round, that dosage is carried to the following round. A person is considered to be choosing a drug treatment if they use any amount of a drug in a round. Based on these selection rules the total number of individuals included is 10,136 and the number of individual rounds is 33,192. The percentage of individual rounds in which statin drugs were used is 36.92%. By comparison, statin drug use in indivudal rounds that were excluded from the sample is less than one percent, 0.57%. The percentage probably represents people with other types or combinations of risk factors such as diabetes, hypertension, or a family history of heart disease who may also be taking statin drugs.

I turn next to a description of the variables of the model. The dependent variables are binary variables: $Drug_{it}$ is equal to 1 if individual i uses statin drugs in period t, and $Drug_{ijt}$, is a binary variable that is equal to 1 if individual i uses drug j in period t. Individual i's state of health in period t is described by four dummy variables: CH_{it} for a cholesterol disorder, HD_{it} for atherosclerotic conditions, DB_{it} for diabetes, and HYP_{it} for hypertension. Since cholesterol levels tend to increase with age, and men are at a higher risk of heart disease at a younger age, I also include the variable Age_i and an indicator for $Male_i$.[23] Finally, individual i's family income

[23] Although one might think of including race, current treatment guidelines specified in NCEP (2001) conclude that treatment should not change by race.

in period t is measured in 1996 dollars as $\text{Log}(\text{inc}_{it})$.[24]

The characteristics of the drugs that are invariant over time are captured using product-specific dummies. The products in the market are: Lipitor, Baycol, Pravachol, Zocor, Lescol, Mevacor and Generic(Mevacor). I use the variable $\log(\text{AgeMolecule}_j)$ to account for the possibility that consumer perception of the molecule of drug j changes over time, perhaps due to advertising.[25]

I use binary variables for insurance coverage. The variable Medins_{it} is equal to 1 if individual i has medical insurance in period t and zero otherwise. Medical insurance coverage typically covers doctor office visits and other services, which makes it more likely that insured individuals will obtain statin drugs and maintain treatment, even when they do not have prescription drug insurance. Individuals on private plans, Medicaid, Medicare, or other public insurance plans are classified as medically insured. I also include individuals with prescription drug insurance coverage because it is rare for individuals with drug insurance not to have medical insurance.

The variable Drugins_{it} is equal to 1 if the individual i has drug insurance in period t and zero otherwise. An individual is classified as having prescription drug coverage if she has a private prescription drug insurance or is on Medicaid. This definition of drug coverage should account for nearly all individuals with drug insurance. According to Health, United States 2005, in 2002, 30% of drug expenditures in the United States are paid out-of-pocket, while private insurance and Medicaid paid nearly all the remaining expenditures. Private insurers and Medicaid accounted for 48% and 18% of drug expenditures, respectively. The remaining 2%

[24] For negative income levels that make up less than .25% of the sample I set income equal to 1,000. A justification for this is that households often overstate self employment expenses because they report capital expenditures in self-employment expenses when only current expenditures should be used.

[25] The age of the molecule is the median date in the current round minus the date in which the molecule was approved for sale by the FDA divided by 365. I add one to the age of the molecule so that the log value starts at zero.

of expenditures were covered by Medicare. To account for the possibility of misreporting by consumers, I use prescription drug expenditure information provided by the MEPS to mark individuals as covered if a third party pays for a significant amount of their drug coverage for the year. I broaden the definition of those with prescription drug insurance by counting individuals as insured if their expenditures on prescription drugs are over $200 a year and over 70% of their expenditures are covered by another party.[26] To check the validity of the prescription drug insurance variable, I looked at payments made by consumers in the sample. The average person with private prescription drug coverage only pays 34.5% out-of-pocket, and the typical person on Medicaid pays approximately 31.5%. Using my definition of drug coverage, I find that those with prescription drug coverage pay 33.3% out-of-pocket, while those that have no prescription drug insurance pay 84.9% out-of-pocket. The fact that people without coverage do not pay the full out-of-pocket price suggests that people are using alternative public sources of coverage such as neighborhood clinics or State programs.

One may worry that the insurance variables are correlated with the consumer-specific unobservables due, say, to an unobserved health condition. Unhealthy people may be more likely to have insurance and purchase prescription drugs. This selection effect would cause an upward bias on the impact of insurance on the demand for drugs. There are three reasons to believe that selection does not pose a major problem. First, the detailed health condition information included in the data accounts for the most important risk factors that would affect the individual's decision to take statin drugs. Second, statin drugs are only a fraction of an individual's total prescription drug expenditure, and the decision to purchase insurance is likely to be based on total expected drug expenditure. Third, in many cases, consumers have a limited choice for insurance coverage because it is often provided by an employer

[26] [6] The $200 is total expenditures including statin drugs and all other types of drugs purchased for a given year.

or the government, and purchasing insurance as an individual rather than through a group plan can be much more expensive.

The price of drug j in period t is denoted $Price_{jt}$. This price is calculated on an annual basis from transactions involving drug j. The task is complicated by the fact that what is observed in the data are transaction prices that vary by the strength of the drug per tablet, which is measured in milligrams, and the size of the bottle, which is measured in number of tablets. For example, Lipitor is available in strengths of 10mg, 20mg, 40mg and 80mg per tablet, and bottle sizes are typically 30, 60 or 90 tablets. Therefore, the number of prices for Lipitor is the number of strengths available times the number of bottle sizes, which in this case, is 12. In order to compare prices across different drugs, I choose a single price for each drug. The price chosen is the one associated with the bottle containing 30 tablets (the most frequently purchased quantity) of the strength that corresponds to a daily dose for the typical consumer who uses that drug (the strength varies across drugs according to their effectiveness).[27] In order to calculate this price, I first take each transaction in period t involving a bottle of 30 tablets of daily dose strength and then divide by the number of tablets in the bottle. This generates a distribution of transaction prices for each drug, since prices vary across locations. $Price_{jt}$ is the median transaction price. I use the median rather than the mean to eliminate the effects of outliers.

There are two important reasons for selecting price points for each drug rather than using an alternative measure of price, such as a price index. First, for drugs that are less frequently purchased (e.g. Baycol) I do not want small movements in the number of people using a particular strength to have a large effect on price estimates. Second, there may be a bias from using a price index rather than price

[27] 7 For the class of statin drugs the usual dose is the initial dose. Looking at the strengths of the drugs, I found that in the initial strength is also the most frequently. This may be the expected cost of individuals.

points when there is entry and exit in the market. For example, when Lipitor enters the market one might expect that people with high LDL levels would switch to Lipitor. This could affect the price index of other drugs even if actual price points do not change.

I compute annual prices rather than prices by round. This is because the prescribed medicines file contains several thousand imputations that involve using average annual wholesale price as the price of the drug rather than the actual transaction price. This is done in cases where the data on expenditures is missing or in cases where prices seem to be outliers.[28] The price calculation by round would be bias toward the average annual wholesale price in each half of the year. For instance, if actual retail prices are rising the entire year, then the bias would be positive in the first half of the year and negative in the second. In fact, when I attempted to estimate price for the first and second half of the year, I found that the price during the year remained relatively flat as might be expected if this bias exists. By imputing annual prices rather than prices in each half of the year, I avoid this type of bias. Future work will look for an alternative sources for price information.

1.4.2 Descriptive Statistics

Table 1.6 provides descriptive statistics on the variables of the model. The second column of the table provides the mean of each variable. A key demographic difference in the sample is the age. The median age is 64 which is much higher than the national median age of about 35. This is not surprising given that cholesterol increases with age as does the incidence of atherosclerotic conditions. The median household income of the selected population is $30,391 which is slightly lower than that of the U.S. population of $35,162.

I find that only 3.4 % of the selected sample have no medical insurance which

[28] [8] A detailed discussion of the imputation process is available in the methodology report at the MEPS website. (http://www.meps.ahrq.gov/).

is a small fraction relative to the national average of about 16 % in 2002. One should expect the sample to have a high level of coverage because nearly half the sample is eligible for Medicare. Relative to the fraction without medical insurance, the fraction without drug insurance is considerably higher, at 29.0%. This, in part, reflects the fact that Medicare provides little prescription drug coverage during the period of the sample.

This table also shows the prevalence of the conditions examined. One can see that all of the selected conditions are relatively common in the sample. It is very common for a person to have a combination of these conditions. I also list the prices of the various products in the market. Looking at the prices of the three top selling drugs Lipitor Zocor and Pravachol, one can see that Zocor and Pravachol are more expensive than Lipitor.

1.5 Results

Before estimating the full choice model, I estimate a probit model of the drug versus no drug choice (i.e., the dependent variable is $Drug_{it}$). This model can be viewed as a simplified version of the demand model in which statin drugs are aggregated into a single product, and the consumers decision is whether or not to buy. Using the probit model, I examine how family income, individual insurance coverage and health conditions affect the decision to use statin drugs. The price in the probit model is a price index based on weighted expenditure shares of each product in the market and include it in the analysis. I also include a linear time trend to account for growth in market demand.[29]

The probit model is estimated with and without random effects. In the random effects model, the probability that an individual i purchases a statin drug

[29] [9] I could have included year dummies to capture trend but then price effects would not be identified since prices are annual.

is given by

$$if>(x_{it}j3 + T_i)$$

where if> is the standard normal distribution, and the unobserved consumer-specific utility T_i is assumed to be normally distributed with mean zero and standard deviaton a_{tau}. In the standard probit, T_i 0. The differences in the estimates provides information on the importance of consumer heterogeneity.

Table 1.7 report the estimates of the two models. The second column report the estimates of the coefficients of the probit model without random effects, and the third column reports their average partial effects. The partial effect is the percent change in the probability evaluated at the population mean. For continuous independent variables, such as price, the marginal probability is calculated for small changes in the independent variable. The change is calculated while the other independent variables in the model are fixed at the mean level of the population. The effect of price on demand for statin drugs is negative and significant. It may be interpreted as the price elasticity of demand for a typical individual in the population. For binary variables, the change in the probability for a typical person is calculated. For doctors insurance, a discrete change in insurance status increases the use of statin drugs by 9.6% for a typical person, and having prescription drug insurance increases demand by an additional 4.4%.[30] Individuals with cholesterol and atherosclerotic conditions are significantly more likely to purchase statin drugs. Finally, individuals who are older, male and with higher income are significantly more likely to use statin drugs. The trend coefficient implies a strong upward trend in demand.

The fourth and fifth column reports the estimates of the coefficients of the random effects probit model and their average partial effects, respectively. The random effects probit differs from the regular probit because it includes a random

[30] 0 Still need to check this partial effect

component, T_i for each individual that is normally distributed and is constant over time. The estimate of a_{tau} is the standard deviation in the population estimates.

The probit models provide useful information about the effect of insurance, income and health conditions on the individual's decision to use statin drugs. However, they are not very informative about market expansion. In particular, it is not clear how much of the market expansion is due to changes in prices, in the demographics of the consumers, or in the choice set of drugs. The discrete choice model addresses this question. The specification that I estimate involves a number of interaction terms. Most plans involve a copayment that is a fixed dollar amount that does not vary with the drug chosen, and to capture this effect, I interact Drugins with a dummy variable tatin. tatin is a variable that is 1 if the option is a statin drug, and 0 otherwise. One would expect this variable to be negative because the copayment is costly to consumers. However, it is also common for insurance plans to induce some price sensitivity through formulary restrictions, tiered copayment structures or a deductible. To allow some flexibility in how insured individuals respond to price, I include an interaction of Price and Drugins. This variable is expected to be positive and less than the mean price coefficient. To capture differences in the cost of visiting a doctor for insured and uninsured individuals, the variable Medins is interacted with tatin. The variables describing the individual's health, age, and gender are also interacted with tatin. Finally, the variables CH and HD are interacted with a dummy variable for each molecule in order to capture the effectiveness of each molecule in treating each condition.[31] Note that the chemical compound for Zocor is left out of the interaction. Zocor must be left out of the interaction to avoid multicollinearity between the tatin and other drug dummy variables. Therefore, the interpretation of the molecule dummy-condition interactions are relative to Zo-

[31] Note that I interact HD and CH with dummies of chemical compound of each drug and not drug dummies. The only difference is that generics for the statin drug Mevacor enter the market in 2002. I assume that the difference in preference between the drug and it's generic equivalent are captured through the product dummy variables.

cor. Finally, I normalize the alternative specific constant on the no-drug treatment choice to zero.

Table 1.8 reports the estimates of the model with no time-invariant, consumer-specific unobservables (i.e., T_{ij} 0). Given this assumption, the model reduces to a conditional logit. Column two reports the coefficient estimates for the model in which the molecule-health condition interactions are excluded, and column four reports the coefficient estimates when the interactions are included. In both models, the coefficient estimates on the variables involving price, income, and insurance have the expected signs and are statistically significant. The market response to price is negative for all income levels. The 75th percentile of log(inc) is approximately 4, so even individuals with high incomes and insurance coverage are sensitive to price. A likelihood ratio test rejects the null hypothesis that molecule-condition interactions are insignificant. The estimates show that Zocor (the molecule left out of the equation) is valued relative to other drugs for the treatment of atherosclerotic conditions, and Baycol, which is not indicated to treat any of the atherosclerotic conditions, is least valued. The Lipitor molecule seems to be preferred by individuals with cholesterol disorders, which one might expect since Lipitor is the most effective drug at lowering LDL cholesterol.

Table 1.9 reports the estimates of the random coefficient model. Recall that this model has random parameters for each product and, in addition, random parameters that allow for correlation over the drug treatment options and over the branded and generic version of Mevacor. That is, there is some component to unobserved utility T_{ij} that is common to all drug treatments and another component that is common for branded and Generic versions of Mevacor. This may be seen by looking at the covariance matrix shown in the appendix. One can see that parameter a_D^2 is the covariance between all statin drug choices. Consequently, 9 random parameters are introduced into the model that were not in the conditional logit.

The results of this model differ significantly from the conditional logit model. The standard deviations of the random-coefficients are highly significant, suggesting that consumer heterogeneity is very important. The only random coefficient that is insignificant is the correlation over the Lovastatin molecule. The fit of the model as measured by the log-likelihood is -24, 241.9, which represents an increase of 12, 550 over the log-likelihood of the conditional logit model. Obviously this is a very significant improvement in the fit of the model as implied by the log-likelihood ratio test. The reason for such a large improvement in the fit is that the model captures additional persistence for users, and it allows for more flexible substitution patterns between the choices.

A key difference between the results of the conditional and mixed logit is that the magnitudes of the parameters increase significantly in the mixed logit specification. The coefficients of many variables increase by a factor of 2 or 3. The most important economic difference between the two models is the change in the relative magnitudes of the coefficients on the insurance and price variables. They imply that insurance and income have a greater impact on the sensitivity of consumers to price when the consumer heterogeneity is taken into account.

1.5.1 Marginal Effects and Cross-Price Elasticities

The calculation of the marginal effects of the insurance variables, income and price are for the last year of the sample, 2002. The choice set at this point includes all of the brands as well as a generic. It is also the year in which the size of the sample is the largest: 3,759 individuals. For the insurance variables, I calculate the percentage change in total use based on a change in insurance coverage. More precisely, for choice j

$$\text{insuranceChange}_j \quad \frac{D_j(\text{insured}) - D_j(\text{Uninsured})}{D_j(\text{Uninsured})}$$

where D_j denotes the market demand for drug j. The income elasticity is based on a 10% increase in income and is calculated as follows:

$$\text{incomeElasticity}_{kj} \quad \frac{\%/:)D_k}{\%/:)inc_i} \;\square\; \frac{D(\log(inc_i * (1 + /:)_{Jnc_i}))) - D(inc_i)}{/:)_{Jnc_i}}.$$

Cross-price elasticities are computed for the un-weighted full sample. I only include one observation for each individual in this year. The change in the expected quantity demanded of drug k when the price of drug j changes by $/:)p_j$ is calculated as follows:

$$\text{PriceElasticity}_{kj} \quad \frac{\%/:)D_k}{\%/:)p_j} \;\square\; \frac{D_i(p_j * (1 + /:)_{p_j})) - D_i(p_j)}{/:)_{p_j}}$$

where $/:)p_j$ is 10 percent.

Table 1.10 shows the results of these calculations for the insurance variables and income. The insurance variables have a significant impact on drug use. An increase in the number of individuals with prescription drug insurance and medical insurance increases demand by approximately 10% and 9% respectively. These results are quite similar to the results of the probit models. A possible reason for why they are slightly higher in the mixed logit model is that these estimates for 2002 when Lipitor is available.[32] The income elasticities are quite small. For example, a 10% increase in income increases drug usage by about 0.26% in the population.

The cross-price elasticities measure the sensitive of consumers to price and the degree of substitutability between the drugs. The first panel shown in table 16 reports estimates of the own and cross-price elasticity. All own-price elasticities are negative and small in absolute value, indicating the demand is inelastic. Demand for Lipitor and Lescol are the most inelastic, followed by Pravachol and Zocor. Demand for the generic version of Mevacor is the most price elastic. In his study of the anti-

[32 2] The marginal effects calculated here are different from the marginal effects in the probit cal- culation. The probit calculation took the marginal effect at a particular point. The estimates here take the change in demand for the entire population.

depressant market, Cleanthous obtains own-price elasticities estimates ranging from -.02 to -.45. My estimates also fall in this range.[33] Our results contrast with earlier work by Stern (1996) and Ellison et al (1997) that find demand for many drugs to be price elastic. The difference may be that our studies account for consumer heterogeneity, and in particular, insurance. Another possibility may be that the drugs analyzed in this paper are mostly branded drugs, and Ellison et al find that price elasticities are typically lower for branded drugs. However, it is impossible to determine the exact reason for this difference because both the data and the methodology vary accross these studies.

The second panel in the table reports estimates of the own and cross-price elasticities when everyone in the sample is given the "typical" prescription drug insurance plan. That is, I simply turn on the prescription drug coverage variable for the entire sample of individuals in 2002. The price elasticities increase considerably. The third panel reports estimates of price elasticities when no one in the sample has prescription drug insurance. A comparison of these two panels of estimates indicates that individuals without drug insurance are on average 5-6 times more price sensitive than individuals with drug insurance.

1.6 Welfare

The goal of this section is to calculate the amount of consumer surplus each product brings to the market. The consumer surplus calculation follows the calculations in Cleanthous (2002) who examines innovation in the antidepressant market.[34] Conditional on observing the random parameters of the model, individual i's consumer

[33] Other studies including Berndt et al (1995) examining the anti-ulcer drug market and Rizzo (1999) looking at anti-hypertensive drugs also find own-price elasticities in the inelastic range.

[34] A paper by Ellickson et al (2000) discusses how to compute the welfare when price sensitivity varies by consumers.

welfare W_i is calculated as:

$$W_i(T_{ij}) \frac{\ln(\sum_{j_t=O}^{J_t} \exp(a_i p_{j\,t} + j3_i x_{j\,t} + T_{ij}))}{-a_i}$$

The above formula is arrived at by integrating over consumer i's demand curve given T_{ij}. Since the random parameters of the model T_{ij} are not observed, I use simulation to estimate the expected surplus of each individual $E_{T_{ij}} W_i^{J_t}$.

There are a number of ways in which surplus from the introduction of a new good can be examined. For instance, one could examine the impact of Lipitor on welfare by examining the gains before and after its entry. However, a number of factors change over time, including factors such as the age and income of the population, prices, and, of course, the choice set. To avoid these problems, I follow the approach taken by Cleanthous (2002) and measure the welfare gains of drug j in a single time period t for good j by calculating the expected surplus with drug j in the market, $EW_i^{J_t}$, and subtract the expected surplus when drug j is excluded, $EW_i^{J^{-j}}$, holding constant the prices of other drugs. (Thus I ignore the effects of a new drug on prices of rival drugs, and the benefits that competition can confer on non-users of the new drug.) Using this approach, I calculate total consumer surplus, $\sum_{i=1}^{N} EW_i^{J_t} - EW_i^{J^{-j}}$ for each drug in the market. I also calculate average consumer surplus above the price of the product for consumers that purchased the product:

$$\text{urplusperuser} \quad \frac{\sum_{i=1}^{N} EW_i^{J_t} - EW_i^{J^{-j}}}{ED_j}$$

Drug insurance complicates the consumer surplus calculation because consumers with insurance do not have to pay the full market price for the drug. To avoid this complication, I calculate consumer surplus for people assuming that they do not have prescription drug insurance. This is also the approach taken by Cleanthous.

Table 1.12 shows the results of the consumer surplus calculations. The first

column of the table shows the price of the drugs in 2002, the second column shows the consumer surplus for the typical consumer that use the product, and the third column reports the ratio of consumer surplus to price. The typical consumers that use Lipitor or Lescol receive the greatest consumer surplus. The oldest drug in the class, Mevacor, and its generic version, generate the lowest consumer surplus. One potential reason is that Merck owns both Zocor and Mevacor, and may have an incentive to keep the price of Mevacor high to push consumers toward Zocor in anticipation of Mevacor going off patent. The branded version of Mevacor generates higher consumer surplus than the generic.

The fourth column shows the ratio of consumer surplus per purchase divided by price. This means that for Zocor that has a ratio of .92 one would expect that the average consumer that purchased Zocor to be willing to spend 92% more than the price. The ratios are fairly stable and average approximately 1 across the goods, with Lipitor and Lescol being the highest. The primary reason for looking at this result is to compare to Cleanthous' work that performs a similar calculation for the antidepressant market. Cleanthous finds this ratio varies significantly with a minimum of 0 and a maximum of 24. The greater diversity in the range of this ratio in Cleanthous' work is likely due to the greater diversity of products in the anti-depressant market relative to the statin class. However, a ratio of 24 for Prozac, a branded drug, implies that consumers are willing to pay 24 times the price of the drug, which seems inconsistent with profit maximizing behavior. The results from my estimates seem more reasonable in magnitude.

Column four of Table 1.13 reports total consumer surplus calculated at the current market price. I quantify the total surplus for consumers at the current price in terms of dollars of surplus per year for the selected sample representing 30 million consumers. Lipitor produces considerably more consumer surplus than the other drugs in the market with approximately 6 billion dollars in surplus a year,

while Zocor, the second highest selling drug brings less than half that. One might argue that Lipitor bringing considerable surplus to the market may be due solely to its lower market price. To check this I look at the consumer surplus assuming that all drugs cost the same amount. At a price of $ 1.15, which is the 2004 average-wholesale-price (AWP) price of generic Mevacor in 1996 dollars, I find that some of the welfare is due to the price, but the consumer surplus from Lipitor is still double that of Zocor's. This result suggests that the innovation of the more effective drug Lipitor is substantial even after controlling for price differences among the products. Another reason for evaluating consumer surplus at a price of $1.15 is that one might think of this as a close proxy to actual marginal cost because one might expect the cost of producing and delivering similar drugs to be the same. Therefore, consumer surplus at the generic price represents the total social welfare from Lipitor. The consumer surplus at the marginal cost is approximately 1 billion dollars greater than the current consumer surplus.

Although the consumer welfare results are interesting, they raise the question of why consumers value these drugs. The three drugs that bring the highest surplus are also the three drugs that have had the highest expenditures on direct-to-consumer (DTC) advertising.[35] I hope to explore this issue in future work.

1.7 Policy Experiments

This section explores the results of two policy experiments. The first section examines how various cost related factors affect market expansion. The second section examines how cost factors affect which drug is chosen. The final section measures the consumer surplus that each product brings to the market in 2002.Drug Costs and Market Expansion Effects

This section examines how cost play a role in consumer's decision of whether

[35] [5] Lipitor, Pravachol and Zocor account for nearly all of the expenditures on DTC advertising.

to purchase a statin drug. Table 1.14 explores a series of policy experiments on a selected cross section of consumers in the sample. Included in the sample are 3,759 people that represent over 30 million people nationally, a representative 8 million of these people do not have prescription drug insurance. The estimates also predict the number of insured individuals taking prescription drugs. The within sample predictions of the number of drug insured and drug uninsured individuals taking prescription drugs are very similar.

The first set of counterfactual policy experiments is on the set of consumers in the sample. In policy experiment 1 I provide all consumers with a typical insurance plan. That is, the dummy variable Drugins is set to 1 for these consumers. I find that this increases the number of users of statin drugs by over 500 thousand people. The next policy experiment is motivated by a study from the U.S. Department of Health and Human Services[36] that estimated that in 1999 cash payers such as those without drug insurance[37] typically pay about 14.6% more than third party payers such as private HMO insurance plans. Frank (2001) provides a more complete discussion of price discrimination in prescription drug retail markets. The reason for price discrimination is that institutions such as insurers and pharmacy benefit managers (PBMs)have buyer power and are able to negotiate significantly lower prices for prescription drugs. Using estimates from the model, I find the market expansion effect from a 15% drop in price for all drugs is 5.8%, representing 300,000 additional users. Frank cites estimates that prices charged to managed care plans purchased via mail order are 30% less than cash payments. To explore this effect on price, policy experiment 3 reduces price in the market by 30%. I find that this increases prescription drug use by 11.65%, which is greater than the expansion from providing prescription drug insurance. The magnitudes of these different effects suggest that controlling prices paid by cash payers may by another effective way of

[36] [6] Report to the President (2000)
[37] [7] This also includes indemnity insurance plans

expanding prescription drug use for those without drug insurance.

Policy experiment 4 examines the effect of removing all cost factors for consumers. In the model this is equivalent to setting Price 0 for all consumers, and assuming that no consumer pays a copayment (i.e. Their is no negative effect on the interaction term for tatin and Drugins). I look at the impact on both consumers with prescription drug insurance and those without. I find that removing cost as a factor expands the number of users for both those with and without drug insurance, but the impact is 18% higher for the uninsured. The difference in the impact is greater than the 9.76% difference, which suggests that income difference between insured and uninsured groups may also be an important factor determining prescription drug use. Overall, I find that removing cost as a factor increases use by 35% which suggests that over 5 million people are not taking drugs because of their cost. While an additional 5 million consumers would take these drugs, there are still approximately 10 million consumers in my sample not taking drugs that are doing so for reasons not related to cost. Note that some caution should be taken in interpreting these results because this is clearly an out-of-sample counterfactual experiment.

Another important question is what type of individuals are affected by market expansion. Table 1.14 makes this comparison for policy experiment 4. The first two columns of the table compare actual health conditions of patients with the predicted health conditions of the group before the policy experiment. One can see that the actual means in the first column are very close to the predicted means in the second. For example the first column shows that 89.27% of the selected population that use statins have a cholesterol disorder. The predicted population that uses statins and has a cholesterol disorder is 89.08%. The third column of the table shows means of the additional users added to the group. The health conditions of the group after costs are set to zero. The third column shows the characteristics

of the consumers after costs are removed. For instance, the first row shows that 70.08% of the 5 million consumers added in the expansion have a cholesterol disorder. Comparing the second and third columns, there are a number of key difference between the groups that use these drugs before the policy experiment and after. One can also see that the fraction of individuals with cholesterol disorders is 19% less in the group of additional users after the experiment; however, the fraction of individuals with an atherosclerotic condition is 10% higher. One potential reason for this is that drugs that have been proven more effective at treating atherosclerotic conditions including Zocor and Pravachol are also more expensive. It may also depend, in part, on the joint distribution of health conditions and insurance coverage since these groups of consumers have distinctly different demographic profiles. As one might expect, the income and insurance coverage is less in the expanded group with doctors insurance coverage being 2% less, drug insurance coverage being 10% less, and average income of about $6,000 less than in the before group.

Focusing on the policy experiment that sets costs to zero I examine the determinants of substitution between products in the market. I find that removing costs as a factor changes the number of consumers purchasing each product, but not by a large amount. I find that Lipitor's shares are just 6% higher. The shares of the more expansive drugs, Pravachol and Zocor increase shares by 3% each. It is somewhat surprising that the generic version of Mevacor also increases, but it is more expensive than Lipitor and Lescol and it's market share is small so only a small increase is necessary to have a large impact on sales.

1.8 Concluslon

The primary finding in this paper is that cost is an important factor determining the number of users of statin drugs in the United States. I find that lower income patients without prescription drug insurance are very price sensitive, they are less

likely to use drugs and, if they do use them, they tend to purchase the less expensive drugs. Insured patients are significantly less sensitive to price.

The policy experiments in this paper quantify the impact of costs nationally and focus on the sample of consumers known to have cholesterol related problems in 2002.[38] My estimates predict that over 500 thousand more consumers with cholesterol problems would take prescription drugs if they had a prescription drug plan. When I remove costs entirely (i.e. a cost of zero for all drugs), I find that the number of consumers without prescription drug insurance that would take statin medication if they were not facing the full price would increase by nearly 50%. If consumers with drug insurance no longer had to pay a co-payments or any portion of their prescription drug bill, I find that the number of insured consumers using statin medications would increase by about 30%. In total, I find that over 5 million consumers with cholesterol related problems in the United States do not take prescription drugs because of the cost.

The types of consumers most impacted by cost factors have less drug and health insurance coverage, lower incomes, and a higher fraction of them have some type of atherosclerotic condition such as heart disease or a history of a stroke or heart attack. Although the impact of costs on the market are large, the magnitudes are not surprising when compared with studies examining compliance rates that find that only 30-40% of consumers prescribed statin drugs still take them after the first year.

I also find that the drug products in the market differ substantially in the level of consumer surplus that they bring to the market. In 2002 I find the largest welfare gains from Lipitor, which are over twice the welfare gains brought by Zocor, the next highest selling drug in the market. Comparing welfare gains at the market price compared to gains at the generic drug price I find significant difference in

[38] Recall that 15% of the statin drug users are excluded from the estimates, so this sample of consumers represents approximately 85% of the consumers of statin drugs nationally.

consumer surplus under the two scenarios. This suggests significant welfare gains from drugs losing their patent.

There are a number of interesting extensions to the current work. The current paper models persistence in consumer use through unobserved heterogneity, and ignores the possibility of state dependence in the market. It may be important to address possibility of state dependence in future work. The model also assumes that there is no product specific unobserved error which could potentially be correlated with price and introduce a bias in the current estimates. An important factor that is unobserved but may affect utility is advertising. There are strong marketing efforts in the statin class of drugs directed toward consumers and doctors. In an extension to the current paper, I will look at how advertising directed toward consumers and doctors affects the overall market demand, and how it differentially affects people with and without insurance and various types of health conditions.

1.9 Appendix

1.9.1 Error Structure

I begin this section by discussing the error structure of the model under the assumption that it is a cross-section, and then discuss the full error structure given the panel data set. The discussion and notation from this section borrows from Ben-Akiva, Bolduc and Walker (2001). The above model specifies a utility function that takes the form:

$$u_{ijt} \quad a_{it}p_{jt} + x_{jt}j3_{it} + T_{ij} + E_{ijt}$$

I enter the T_{ij} into the model using an error component framework. I specify unobserved component of the model as taking the following form for T_i and E_{it} vectors of size J_t:

$$T_i + E_{it} \quad F_t r(_{it} + E_{it}$$

where F_t is a $J_t \times M_t$ matrix of factor loadings with values in the matrix taking on values of zero or one. The parameter r is a $M_t \times M_t$ matrix and $(_i$ is a M_t vector of normally distributed errors. The covariance of the J_T vector of utilities u_{it} takes the form:

$$'L, \quad \mathrm{cov}(u_{it}) \quad \mathrm{Cov}(T_{ij} + E_{ij}) \quad F_t r r^t F^t_t + E_{it}E_{it}$$

The E_{it} are independent across choices and I normalize the variance of the extreme values to $w^2/6$ which gives the usual logit specification. The covariance matrix is then:

$$'L, \quad \mathrm{Cov}(T_{ij} + E_{ij}) \quad F_t r r^t F^t_t + w^2/6 i_{J_T}$$

where i_{J_T} is the identity matrix of size $J_T \times J_T$. In the above application I assume that

$$\begin{matrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{matrix}$$

F

The matrix r is the diagnol:

$$\begin{pmatrix} a_{Lip} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & a_{Bay} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & a_{Le} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & a_{MevG} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & a_{MevB} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{Pra} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & a_{Zoc} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & a_{ND} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & a_{D} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & a_{Lov} \end{pmatrix}$$

r

The variance-covariance matrix is then:

'L,

$$
\begin{bmatrix}
\sigma^2_{Lip} + \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & 0 \\
\sigma^2_D & \sigma^2_{Bay} + \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & 0 \\
\sigma^2_D & \sigma^2_D & \sigma^2_{Les} + \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & 0 \\
\sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_{MevG} + \sigma^2_{Lov} + \sigma^2_D & \sigma^2_D + \sigma^2_{Lov} & \sigma^2_D & \sigma^2_D & 0 \\
\sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D + \sigma^2_{Lov} & \sigma^2_{MevB} + \sigma^2_D + \sigma^2_{Lov} & \sigma^2_D & \sigma^2_D & 0 \\
\sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_{Pra} + \sigma^2_D & \sigma^2_D & 0 \\
\sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_D & \sigma^2_{Zoc} + \sigma^2_D & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_{ND}
\end{bmatrix}
$$

$$
\begin{bmatrix}
(7r^2/6) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & (7r^2/6) & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & (7r^2/6) & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & (7r^2/6) & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & (7r^2/6) & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & (7r^2/6) & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & (7r^2/6) & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & (7r^2/6)
\end{bmatrix}
$$

The first matrix is the covariance matrix of T_i, and the second component is the covariance matrix of the logit errors $(w^2/6) \quad i_{J_T}$.

To extend the variance-covariance matrix to the panel setting is straightforward, one simply uses the fact that E_{ijt} are independent. If two periods are observed then the variance-covariance matrix is:

$$
\begin{bmatrix}
F rr^t F^t + (w^2/6) i_{J_T} & F rr^t F^t \\
F rr^t F^t & F rr^t F^t + (w^2/6) i_{J_T}
\end{bmatrix}
$$

1.9.2 Identification

To keep matrices a reasonable size, I go through the proof of identification and normalization for a smaller version of the model. The smaller version examines identification in 1996 when there are only 4 products in the market. A similar proof follows when using the full variance-covariance matrix. I follow the steps described in [1] in checking that the parameters of the model are identified.

It is well known in discrete choice models that the level of utility has no effect on consumers decisions, so I begin by subtracting the utility matrix from choosing No – drug in order to set the level of utility. I find that the "difference" variance-covariance matrix assuming a cross section is:

/:)'L,

$$\begin{bmatrix} a^2_{Les}+a^2_D+a^2_{ND}+2(7r^2/6) & a^2_D+a^2_{ND}+(7r^2/6) & a^2_D+a^2_{ND}+(7r^2/6) & a^2_D+a^2_{ND}+(7r^2/6) \\ a^2_D+a^2_{ND}+(7r^2/6) & a^2_{MevB}+a^2_D+a^2_{ND}+2(7r^2/6) & a^2_D+a^2_{ND}+(7r^2/6) & a^2_D+a^2_{ND}+(7r^2/6) \\ a^2_D+a^2_{ND}+(7r^2/6) & a^2_D+a^2_{ND}+(7r^2/6) & a^2_{Pra}+a^2_D+a^2_{ND}+2(7r^2/6) & a^2_D+a^2_{ND}+(7r^2/6) \\ a^2_D+a^2_{ND}+(7r^2/6) & a^2_D+a^2_{ND}+(7r^2/6) & a^2_D+a^2_{ND}+(7r^2/6) & a^2_{Zoc}+a^2_D+a^2_{ND}+2(7r^2/6) \end{bmatrix}$$

I then check the order and rank conditions of /:)'L,. The order condition states that the number of parameters that can be identified is equivalent to the number of cells in /:)'L, matrix minus one. This number is 15 and the number of parameters is is only 6, so this condition is satisfied. To check the rank condition I take a vector of all the unique components of the above covariance matrix and determine if the parameters are identified. The matrix is

$$W \begin{bmatrix} a^2_{ND}+a^2_{Le}+a^2_D+2(w^2/6) \\ a^2_{ND}+a^2_{MevB}+a^2_D+2(w^2/6) \\ a^2_{ND}+a^2_{Pra}+a^2_D+2(w^2/6) \\ a^2_{ND}+a^2_{Zoc}+a^2_D+2(w^2/6) \\ a^2_{ND}+a^2_D+(w^2/6) \end{bmatrix}$$

Using the fact that the logit errors are independent across observations gives another set of unique components to the full variance covariance matrix that is not observed

in the cross section:

$$\begin{bmatrix} a_{ND}^2 + a_{Le}^2 + a_D^2 & a_{ND}^2 & a_{ND}^2 & a_{ND}^2 & a_{ND}^2 \\ a_{ND}^2 & a_{ND}^2 + a_{MevB}^2 + a_D^2 & a_{ND}^2 & a_{ND}^2 & a_{ND}^2 \\ a_{ND}^2 & a_{ND}^2 & a_{ND}^2 + a_{Pra}^2 + a_D^2 & a_{ND}^2 & a_{ND}^2 \\ a_{ND}^2 & a_{ND}^2 & a_{ND}^2 & a_{ND}^2 + a_{Zoc}^2 + a_D^2 & a_{ND}^2 \\ a_{ND}^2 & a_{ND}^2 & a_{ND}^2 & a_{ND}^2 & a_{ND}^2 + a_D^2 \end{bmatrix}$$

The jacobian matrix of unique elements corresponding to the above unique elements of the covariance matrix is:

$$\{ {}^2_{Le},\quad a^2_{MevB},\quad a^2_{Prav},\quad a^2_{Zoc},\quad a^2_{ND},\quad a^2_D,\quad (w^2/6)\}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 1 & 2 \\ 0 & 1 & 0 & 0 & 1 & 1 & 2 \\ 0 & 0 & 1 & 0 & 1 & 1 & 2 \\ 0 & 0 & 0 & 1 & 1 & 1 & 2 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

The rank of the above matrix is 6, and the requirement to normalize one parameter for scale implies that 5 parameters can be identified.[39] There are 6 parameters in the above model, so I normalize T_{iND} to a standard normal so a^2_{ND} 1 and the 5 remaining parameters of the model can be identified.

[39] The logit variance is already normalized to $K^2/6$).

1.10 Tables

Table 1.1: **Statin Drug Characteristics**

Brand Name	Usually Daily Dose*	Avg. Drop in LDL per Avg. Daily Dose**	Avg. Drop in LDL per Max Dose**
Mevacor	20 mg	24	40
Mevacor (Generic)	20 mg	24	40
Pravachol	20 mg	32	37
Zocor	10 mg	30	47
Lescol	20 mg	22	35
Lipitor	10 mg	39	60
Baycol	0.4 mg	34	42

Notes:

*The usual daily dose information and average drop in LDL cholesterol and MAX LDL drop were retreived from the drug label

**Usual Daily Dose specified in the Drug Facts & Comparisons handbook.

Table 1.2: **Conditions that the Following Drug Molecules are Indicated to Treat***

Drug Comparisons	Atorvastatin (Lipitor)	Cerivastatin (Baycol)	Fluvastatin (Lescol)	Lovastatin (Mevacor)	Pravastatin (Pravachol)	Simvastatin (Zocor)
Cholesterol Disorders						
can be used for hypercholesterolemia?	yes	yes	yes	yes	yes	yes
can be used for hyperlipoproteinemia?	yes	yes	yes	yes	yes	yes
can be used for hypertriglyceridemia?	yes	yes†	yes	no	yes	yes
Atherosclerotic Conditions (e.g. Related to Heart Disease or stroke)						
can be used for atherosclerosis?	no	no	yes	yes	yes	yes
can be used for myocardial infarction prophylaxis?	yes	no	yes	yes	yes	yes
can be used for postmyocardial infarction?	no	no	no	no	yes	no
can be used for stroke prophylaxis?	no	no	no	yes†	yes	yes

Note:

*This information is from: Clinical Pharmacology Copyright 2005

† indication not approved by the FDA

Table 1.3: **User Shares***

Drug	1996	1997	1998	1999	2000	2001	2002
Lipitor		15.7%	31.9%	37.9%	41.5%	44.1%	47.1%
Baycol			2.0%	3.9%	5.2%	7.2%	
Lescol	14.5%	16.2%	10.8%	6.8%	4.8%	3.8%	4.8%
Mevacor	22.6%	14.5%	7.8%	5.9%	5.8%	3.7%	1.6%
Mevacor (Generic)							4.6%
Pravacol	29.2%	21.7%	19.2%	17.4%	15.0%	12.7%	12.7%
Zocor	33.8%	31.9%	28.2%	28.1%	27.8%	28.1%	29.3%

Tot. Predicted # Users in Millions:	6.26	8.44	11	12.6	15.6	19	21.8
Estimated % Annual Growth in Users	•	+34.82%	+30.33%	+14.55%	+23.81%	+21.79%	+14.74%

*User shares derived from MEPS data. Use individual provided by MEPS to derive shares.

Table 1.4: **Condition Classifications**

	Condition	CCCODEX	ICD • 9 Codes
Atherosclerotic Condtions	Acute myocardial infraction		410
	Other acute and subacute form of ischemic heart disease		411
	Old myocardial infarction		412
	Angina pectoris		413
	Other forms of chronic ischemic heart disease		414
	Occlusion and stenosis of precerebral arteries		433
	Occlusion of cerebral arteries		434
	Transcient cerebral ischemia		435
	Acue but ill•defined cerebrovascular disease		436
	Other and ill•defined cerebrovascular disease		437
	Atherosclerosis		440
	Arterial embolism and thrombosis		444
	Coronary atherosclerosis and other heart disease	101	
	Other and ill•defined heart disease	104	
	Congestive heart failure, nonhypertensive	108	
	Acute cerebrovascular disease	109	
	Late effects of cerebrovascular disease	113	
	peripheral and visceral atherosclerosis	114	
	Aortic and peripheral arterial embolism or thrombosis	116	
Cholesterol Disorder	Disorders of the lipoid metabolism		272
Hypertension	Essential Hypertension		401
Diabetes	Diabetes		250

Table 1.5: **Comparison of IMS data and MEPS Revenue Share**

Comparision: IMS Revenue Share & MEPS Revenue Share

IMS Revenue Share		1999	2000	2001	2002
	Lipitor	41.46%	45.99%	46.94%	48.94%
	Pravachol	16.30%	14.43%	14.08%	14.36%
	Zocor	31.68%	30.83%	31.80%	32.80%

Meps Revenue Share		1999	2000	2001	2002
	Lipitor	41.34%	42.77%	48.56%	46.00%
	Pravachol	17.47%	16.14%	14.54%	15.85%
	Zocor	28.95%	29.16%	28.56%	32.80%

Error in Predicted Share		1999	2000	2001	2002
	Lipitor	0.12%	3.22%	•1.62%	2.94%
	Pravachol	•1.17%	•1.72%	•0.46%	•1.49%
	Zocor	2.73%	1.67%	3.24%	0.00%

Table 1.6: **Demographics • Age, Income and Sex**

Variable	Mean	25th Percentile	50th Percentile	75th Percentile
Age	63	53	64	74
Household Income ($1996)	$41,161	$14,162	$30,391	$55,800
Log(Income ($1996)/1000)	3.275	2.651	3.414	4.022
Male (Male=1, Female=0)	0.477			
No Medical Insurance	0.034			
Medical Insurance & No Drug Insurance	0.290			
Medical Insurance & Drug Insurance	0.675			
CH (Cholesterol)	0.590			
HD (Atherosclerotic)	0.560			
DB (Diabetes)	0.236			
HYP (Hypertension)	0.508			
Price				
Lipitor	1.782			
Baycol	1.303			
Lescol	1.238			
Mevacor	2.123			
Generic	2.069			
Pravacol	2.134			
Zocor	2.020			
Observations				
# Individuals	10,136			
# Individual Rounds	33,192			

Table 1.7: **Probits**

# of Observations 33,192
# of Individuals 10,136

	Probit		R.E. Probit	
Variable	Coef.	% Change	Coef.	% Change
Price Index	•0.865	•0.310	•0.943	•0.246
	•(3.71)	•(3.71)	•(2.86)	•(2.86)
MedIns.	0.287	0.096	0.368	0.081
	(4.38)	(4.38)	(3.72)	(4.53)
DrugIns	0.123	0.044	0.245	0.061
	(4.58)	(4.58)	(5.90)	(6.12)
Log(Inc)	0.059	0.021	0.068	0.018
	(5.46)	(5.46)	(4.14)	(4.12)
CH	1.426	0.452	2.607	0.551
	(40.61)	(40.61)	(39.42)	(45.15)
HD	0.269	0.096	0.432	0.110
	(8.52)	(8.52)	(7.72)	(7.81)
DB	0.037	0.013	0.095	0.025
	(1.37)	(1.37)	(1.99)	(1.94)
HYP	0.064	0.023	0.101	0.026
	(2.68)	(2.68)	(2.46)	(2.46)
Age	0.117	0.042	0.213	0.056
	(16.67)	(16.67)	(17.54)	(18.08)
Age^2	•0.088	•0.032	•0.162	•0.042
	(15.63)	•(15.63)	•(16.31)	•(16.80)
male	0.140	0.050	0.255	0.067
	(5.95)	(5.95)	(6.18)	(6.15)
Linear Trend	0.132	0.047	0.198	0.052
	(8.92)	(8.92)	(9.16)	(9.09)
Contstant	•4.619		•9.252	
	•(10.39)		•(13.80)	
σ			1.484	
			(54.191)	
Log•likelihood	•17,518.3		•14,665.3	

Table 1.8: **Conditional Logit (Without Random Coefficients)**

# of Observations	33,192
# of Individuals	10,136

variables	Coef.	Asy•Z	Coef.	Asy•Z
Price	•1.223	•(8.54)	•1.207	•(8.42)
Price*Drug Ins.	0.392	(5.28)	0.421	(5.66)
Drug Ins.*Drug	•0.503	•(3.48)	•0.560	•(3.85)
Price*log(Inc)	0.058	(8.59)	0.059	(8.75)
Doctor Ins.*Drug	0.375	(4.63)	0.376	(4.65)
Statin*CH	2.480	(54.83)	2.500	(40.63)
Statin*HD	0.465	(12.37)	0.623	(12.89)
Statin*age	0.020	(18.16)	0.020	(18.17)
Statin*Male	0.259	(9.71)	0.258	(9.66)
Statin*HYP	0.252	(8.03)	0.252	(8.02)
Statin*DB	0.157	(4.97)	0.157	(4.96)
Lipitor*HD			•0.216	•(4.41)
Baycol*HD			•0.732	•(4.36)
Lescol*HD			•0.473	•(5.07)
Mevacor (+Gen.)*HD			•0.018	•(0.21)
Pravachol*HD			•0.189	•(2.94)
Lipitor*CH			0.125	(1.78)
Baycol*CH			•0.565	•(2.61)
Lescol*CH			•0.360	•(2.91)
Mevacor(+Gen.)*CH			0.096	(0.78)
Pravachol*CH			•0.236	•(2.73)
Zocor	•5.793	•(22.46)	•5.896	•(22.58)
Lipitor	•4.699	•(19.09)	•4.822	•(19.25)
Mevacor	•7.865	•(29.98)	•8.040	•(28.12)
Pravachol	•6.359	•(23.51)	•6.188	•(22.29)
Lescol	•7.597	•(39.65)	•7.177	•(32.40)
Baycol	•7.319	•(34.54)	•6.649	•(22.25)
Mevacor (Generic)	•8.135	•(31.75)	•8.301	•(29.58)
log(AgeMolecule)	1.103	(23.52)	1.090	(23.23)
Log•likelihood	•36,835.8		•36,791.6	

Table 1.9: **Mixed Logit**

# of Observations	33,192
# of Individuals	10,136

variables	Coef.	Asy•Z
Price	•1.567	•(3.94)
Price*Drug Ins.	1.042	(4.46)
Drug Ins.*Statin	•1.491	•(3.29)
Price*log(Inc)	0.083	(4.63)
Med Ins.*Statin	0.627	(2.78)
Statin*CH	5.777	(24.43)
Statin*HD	1.326	(7.01)
Statin*age	0.047	(13.07)
Statin*Male	0.693	(7.53)
Statin*HYP	0.551	(4.93)
Drug*DB	0.475	(4.45)
Lipitor*HD	•0.328	•(1.35)
Baycol*HD	•1.353	•(3.76)
Lescol*HD	•1.172	•(2.52)
Mevacor (+Gen.)*HD	•0.481	•(1.63)
Pravachol*HD	•0.508	•(1.69)
Lipitor*CH	1.246	(3.73)
Baycol*CH	•2.280	•(5.08)
Lescol*CH	•1.444	•(2.77)
Mevacor(+Gen.)*CH	•1.714	•(4.91)
Pravachol*CH	•0.458	•(1.26)
Statin	•16.211	•(20.58)
Lipitor	1.467	(3.30)
Baycol	0.871	(1.04)
Lescol	•4.982	•(5.56)
Mevacor	•4.392	•(6.74)
Mevacor (Generic)	•1.357	•(1.58)
Pravachol	•2.645	•(4.71)
log(AgeMolecule)	2.075	(16.52)
S.D.		
Statin	1.589	(14.40)
Lipitor	4.809	(33.40)
Baycol	3.574	(9.62)
Lescol	6.194	(18.95)
Mevacor	5.075	(16.63)
Mevacor (Generic)	3.033	(6.81)
Pravachol	5.577	(24.82)
Mevacor (Molecule)	0.241	(1.21)
Zocor	4.317	(32.91)
Simulation Draws	200	
Log•likelihood	•24,241.9	

Table 1.10: **Insurance and Income Marginal Effects (2002)**

	Change Pres Drug Insurance	Change Doctors Insurance	Income Elasticity
Drug	**10.07%**	**9.01%**	**0.026**
Lipitor	7.89%	9.68%	0.0212
Lescol	•11.84%	12.41%	0.0103
Mevacor (Generic)	23.29%	23.11%	0.0509
Mevacor	28.04%	15.59%	0.043
Pravachol	22.98%	11.46%	0.0337
Zocor	18.23%	12.42%	0.0322

Table 1.11: **Cross•Price Elasticity (2002)**

Market Cross•Price Elasticities							
	Lipitor	Lescol	Mevacor (Generic)	Mevacor	Pravachol	Zocor	No Drug
Lipitor	•0.238	0.070	0.097	0.070	0.061	0.068	0.064
Lescol	0.007	•0.254	0.012	0.009	0.007	0.008	0.008
Mevacor (Generic)	0.010	0.013	•0.564	0.016	0.011	0.013	0.014
Mevacor	0.009	0.011	0.019	•0.447	0.009	0.011	0.012
Pravachol	0.022	0.026	0.040	0.028	•0.352	0.025	0.026
Zocor	0.043	0.050	0.080	0.055	0.045	•0.337	0.050

Cross Price Elasticities • Simulate Everyone having No Insurance							
	Lipitor	Lescol	Mevacor (Generic)	Mevacor	Pravachol	Zocor	No Drug
Lipitor	•0.592	0.154	0.250	0.183	0.157	0.170	0.143
Lescol	0.017	•0.564	0.032	0.023	0.019	0.020	0.019
Mevacor (Generic)	0.023	0.027	•1.439	0.037	0.027	0.031	0.030
Mevacor	0.020	0.022	0.043	•1.164	0.022	0.025	0.024
Pravachol	0.051	0.054	0.096	0.068	•0.915	0.061	0.055
Zocor	0.101	0.109	0.198	0.137	0.112	•0.866	0.108

Cross Price Elasticities • Simulation Everyone having Insurance							
	Lipitor	Lescol	Mevacor (Generic)	Mevacor	Pravachol	Zocor	No Drug
Lipitor	•0.111	0.032	0.049	0.036	0.031	0.034	0.030
Lescol	0.003	•0.113	0.006	0.004	0.003	0.003	0.004
Mevacor (Generic)	0.005	0.007	•0.281	0.009	0.006	0.007	0.007
Mevacor	0.005	0.006	0.010	•0.224	0.005	0.006	0.006
Pravachol	0.012	0.013	0.021	0.015	•0.172	0.014	0.013
Zocor	0.022	0.025	0.042	0.029	0.024	•0.162	0.025

Table 1.12: **Consumer Surplus Estimates***

	In Sample	Rep. In Population
Sample Size:	3,759	30,740,077
Actual # Users:	1,847	15,746,264
Pred. # Users:	1,824	15,358,263

Drug Name	Price in 2002	Surplus per User in 2002 Price	Per User Surplus to Price Ratio	Total Consumer Surplus (No Insurance)	Total Consumer Surplus at Generic Price**	Total Consumer Surplus at Full Insurance***
Lipitor	$2.01	2.57	1.28	$6,060,373	$7,225,370	$8,869,061
Lescol	$1.38	2.10	1.52	$795,558	$710,488	$899,481
Mevacor (Generic)	$2.07	1.20	0.58	$268,758	$401,913	$613,528
Mevacor	$2.30	1.67	0.72	$379,792	$577,209	$772,285
Pravachol	$2.35	2.12	0.90	$1,409,002	$2,012,533	$2,510,747
Zocor	$2.20	2.02	0.92	$2,616,577	$3,598,817	$4,623,923

*All estimates in 1996 $s. Total consumer surplus calculations in thousands of dollars
**I assume a generic price of a $1.15 based on a 2004 average wholesale price of generic Mevacor in 1996$
***Full insurance implies a zero price

Table 1.13: **Average Statistics on Selected Populations Before and After Full Insurance Experiment**

	In Sample	**Rep. In Population**
Sample Size:	3759	30,740,077
# Drug Uninsured	1089	8,847,364
# Drug Insured	2670	21,892,713
Actual # Drug Unins. Users:	485	4,086,135
Pred. # Drug Unins. Users:	471	3,928,966
Actual # Drug Ins. Users:	1362	11,660,129
Pred. # Drug Ins. Users:	1353	11,429,298

	% Increase in # of Users	Total Predicted Additional Users
Drug Uninsured		
1. Typical Insurance	9.76%	506,778
2. 15 % Drop in Price	5.80%	301,295
3. 30 % Drop in Price	11.65%	605,092
4. Full Insurance (No Cost)	48.67%	1,912,341
Drug Insured		
4. Full Insurance (No Cost)	30.35%	3,468,321
Market Total		
4. Full Insurance (No Cost)	35.03%	5,380,662

Table 1.14: **Average Statistics on Selected Populations Before and After Full Insurance Experiment**

	Actual Mean	Predicted Mean Before	Predicted Mean Additional Users
Cholesterol	89.27%	89.08%	70.08%
Athero. Disorder	34.90%	36.16%	44.56%
Diabetes	22.96%	23.68%	21.51%
Hypertension	54.05%	54.69%	50.07%
Drug Ins	74.05%	74.42%	64.46%
Health Ins	98.39%	98.35%	96.78%
Income	$50,408	$49,535	$43,501
Age	62.9	62.6	62.9
Male	53.49%	54.34%	49.00%

Chapter 2

Decomposing the Expansion Effects of Direct-to-Consumer Advertising

2.1 Introduction

In 1997 the Food and Drug Administration changed the required content of prescription drug television advertisements which effectively lowered the cost of advertising.[1] Since the regulation change there has been a tremendous increase in advertising for pharmaceutical drugs directed toward consumers. From 1996 to 2002 expenditure on direct-to-consumer advertising (DTCA) increased 600%, reaching over 2.5 billion dollars in total expenditures by 2002. Recent empirical evidence has linked this growth in DTCA to market expansion in demand for several classes of drugs. However, little is known about how the responsiveness of DTCA varies across individuals in the market. This paper examines: Who is responding to advertising? What type

[1] The rule change reduced the amount of information the companies were required to disclose in the ad. Now instead of a detailed listing of effectiveness, contradictions and side-effects of the drugs the ads only require "major statements" of the most important characteristics.

of advertising are they responding to? and How they are responding? I attempt to answer these questions by estimating a dynamic demand model that explores the heterogeneous effects of DTCA on individual demand for anti-cholesterol drugs.

Although this paper explores a variety of factors that may affect individual responsiveness, it primarily focuses on the impact DTCA has on two types of individuals - those that have recently purchased (individuals on the medication) and those that have not (individuals off the medication). The effect of advertising on these two groups helps in understanding the incentives of firms to use DTCA. Since many drugs are used by individuals over a long period of time, current advertising can affect future demand through persistence in individual use. At one extreme, if only those not on medication respond to DTCA and there is strong persistence in use, firms will have an incentive to advertise early to get people started on the medication. At another extreme, if only those on medication respond to DTCA then there is greater incentive to use advertising only after the population of individuals using the drug grows. Estimates from this paper account for the dynamic component of the individual purchase decisions and provide an important first step in calculating the optimal supply of DTCA.

Another reason to study the response to DTCA for those that recently purchased and those that have not is that the effect on these populations provide some clues about the nature of DTCA. If those on the medication are fully informed by doctors and pharmacists and advertising is solely informative, then additional advertising should have no effect on these individuals. On the other hand, if advertising does affect their decision to purchase this indicates that DTCA is not solely informative or that advertising continues to inform individuals even after being treated.[2] Compared to individuals taking the drug, those not on a drug may

[2] Ads may create a deeper understanding of the usefulness of the drugs, their side effects and remind people to take their medication. The ads may also persuade consumers, perhaps through dramatically instilling fear of future health risks.

have less contact with doctors and pharmacists so DTCA may be a more important source of information.

This paper contributes to the recent literature examining the effects of DTCA by exploring the heterogenous effects of DTCA on market expansion. I focus on the statin class of anti-cholesterol drugs because the DTCA expenditures in this class are among the largest with over 200 million spent in 2002. In addition, the large expenditures on advertising were accompanied by significant market expansion. From 1996 to 2002 the number of users of statin drugs increased approximately 244% from an estimated 6 million people purchasing a statin drug to 22 million.[3] The dynamic component of demand may be important for the statin class because they are typically prescribed to be taken daily and indefinitely. However, it is unclear how important the dynamic effect is because there are no symptoms from having high cholesterol and several studies have found that patients often stop taking their cholesterol medication despite the health consequences.[4]

To identify the effects of DTCA I combine nationally representative panel data with monthly DTCA expenditure data. I aggregate over all products in the statin class and assume that individuals make the discrete choice of whether to start or stop taking a drug. The econometric model allows for the start/stop choice to depend on observable characteristics of the individual (e.g. health conditions, insurance coverage, the price of the drug, and DTCA), unobservable individual-specific characteristics, and the individual's past choice. I employ an approach proposed by Wooldridge (2004) to estimate the dynamic econometric model that separately identifies the effect of the consumer's past choice (state dependence)

[3] The estimates include any individual that purchased at least once sometime in the year, so it may overstate the actual number of users at one point in time. The estimate is based on calculations from the MEPS data discussed later in this paper.

[4] Studies have shown that approximately 50% of those that begin statin drug therapy have stopped 6 months after treatment.NCEP (2001). The health consequences are serious because high cholesterol is a major contributor to the development of heart disease, the leading cause of death in the United States.

from unobserved characteristics of the consumer (unobserved heterogeneity).

Limiting the individual's decision to a binary choice is a key simplifying assumption of the econometric model. This assumption contrasts with other papers that assume individuals choose between a larger set of products.[5] There are two reasons to make this simplifying assumption. First, when an individual is being treated by a doctor the amount of control that she has over the drug choice is unclear since the doctor writes the prescription, so focusing on the binary decision may fit more closely with the decision that the patient actually makes. Second, modeling the binary choice is sufficient to examine the market expansion effects of DTCA and it is computationally simpler than a dynamic differentiated product model. The trade-off of this simplifying assumption is that I cannot structurally identify some important factors that may influence demand such as changes in the set of differentiated products available in the market or the characteristics of specific products that change over time.

Estimates from this paper produce a number of interesting results. I find that DTCA has a positive effect on demand, but it is relatively more effective at bringing consumers into the market than retaining consumers that were on the medication. The overall short-term market elasticity of demand is 0.107, the elasticity for the population not on any drug is 0.159, and the elasticity for those on a drug is 0.086. I also find some dynamic effects from DTCA from persistence in consumer use. The market demand elasticity decline but remain positive for several months in the future.

Further analysis shows some interesting heterogeneous effects from advertising. I find that age, the price of the drug and income have no effect on individual responses to DTCA. However, I find that those without medical insurance, those that may be unaware of their health condition, and those with less education are

[5] E.g. Chapter 1 of this dissertation examining the decision to take a drug or not, and if so, which drug to take.

more responsive to DTCA. To the extent one may consider these groups less informed, these results are consistent with DTCA having the greatest impact on the least informed populations.

The paper is organized as follows: The next section reviews the current literature. The following section discusses some features of the market for cholesterol drugs and direct-to-consumer advertising. I then specify the econometric model and the approach taken to identify DTCA. Subsequently, I describes the data used in the estimation. In the final two sections I provide results and conclude.

2.2 Literature Review

Much of the literature examining the demand effects of DTCA has centered around measuring the expansion effects versus the business stealing effects of advertising. Market expansion effects are generally considered to be welfare enhancing as individuals learn about new treatment options. However, there are often concerns over business stealing effects that could unnecessarily lead consumers to purchase overly expensive and potentially less effective drugs than they are currently taking. The current literature has generally shown that there are market expanding effects of DTCA, but limited business stealing effects (See Ling and Berndt (2002), Donohue and Berndt (2004), Narayanan et al (2004), Wosinska (2002), and Iizuka and Jin (2005b). Also see Berndt (2005) for a more complete review of this literature). The focus of this paper is on the market expansion effect of advertising and the remainder of this literature review looks at papers that provide measurements of these effects.

A number of studies measuring the market expansion effects from advertising use aggregate data. One of the earlier studies on DTCA looking at the statin drug market is Calfee et al (2002). They estimate demand for the statin drug class using aggregate data from 1995-2000. They find that DTCA did not directly increase

total market demand, but found some evidence that television advertising may be strengthening patient compliance. Rosenthal et al (2003) estimate the demand effects of advertising using monthly market share data from 1996 to 1999 across a number of different drug classes. They apply an AIDS demand model using an IV approach and find that DTCA has a significant effect on market expansion that spill over to all drugs within a class, but find no evidence of business stealing effects between drugs within a class. Iizuka and Jin (2005a) measure market expansion by looking at the impact of DTCA on doctor visits in the U.S. using visit information from the National Ambulatory Medical Care Survey (NAMCS) and monthly DTCA data. They observe the aggregate visit information by condition and match this DTCA data for drug classes that treat the condition. They find that DTCA has a significant effect on visits to the doctor in the U.S. In addition, they disaggregate the visit information to aggregate number of visits for different subpopulations. Their key findings on the heterogeneous effects of DTCA for these subpopulations are that those with HMO insurance are less responsive than Non-HMO individuals, and that elderly respond less to DTCA; but they do not find statistically significant differences between any of these subpopulations. My paper builds on the above literature by providing national estimates of the market expansion effects of DTCA based on consumer level data. Estimates of market expansion at the consumer level are especially important for obtaining precise estimates of the heterogenous effects of DTCA.

The literature using micro data that provide evidence of the expansion effects of advertising have used claims data. Donohue et al (2004) focus on the effects of advertising on two types of individuals. They look at individuals that have a condition and are deciding whether to take a drug, and the decision to complete treatment for those that have started. They separately analyze these two decisions for anti-depressant drugs using a logit model. The data used in their study includes

medical claims data combined with monthly advertising data. They find that those diagnosed in a period in which spending on DTCA was high were more likely to initiate therapy. In addition, they find that total class expenditures on DTCA have had a significant positive impact on completing treatment. Wosinska (2004) studies the effect of DTCA on compliance. Her data is claims information on privately insured individuals in California. She measures compliance using the number of noncompliant days in a month. She finds that compliance effects are small, they tend to spill over to other brands, and in certain instances, DTCA advertising may actually have a negative impact on compliance. This study adds to the studies using consumer level data by using nationally representative data and accounting for the dynamic effects of advertising on individual demand. Using nationally representative data may be especially important for the statin drug class because about half of the people that use statins are over the age of 65 and are covered by the public insurance program Medicare who may not be included in the claims data. The data used in this paper also allow me to look at the heterogeneous effects of DTCA that is not possible using claims data that typically has limited demographic information.

2.3 Market For Cholesterol Drugs and DTCA

From a firms perspective, the possible gains from DTCA in the cholesterol drug market are considerable because high cholesterol is a prevalent condition in the U.S. with an estimated 17% of individuals over the age of 20 classified as having high cholesterol.[6] In addition, high cholesterol is perceived as undertreated by many in the medical community. Topel (2004) estimates that approximately 36 million people could benefit from using these drugs which is well below the number treated

[6] The statistic is reported in Health, United States (2005) High cholesterol is defined as serum cholesterol levels of 240 or higher. This statistic is a projection of the number of individuals that have high cholesterol, so the number that are aware that they have a cholesterol problem is less.

over the sample period.

Relative to other cholesterol drug treatments, the statin drug class has been particularly well positioned to gain from market expansion. Statins have been shown to be most effective at lowering cholesterol with fewer side effects than alternative drug therapies and they are typically the drug of first choice by physicians for the treatment of high cholesterol.[7] For most of the sample period all the drugs in the statin class were under patent protection, so there were no generics competitors. As a result, the statin drugs have been relatively expensive with a price of around $700 for a years supply, suggesting the revenue gains from market expansion are considerable.

As mentioned before, the statin drug class has grown significantly with the number of users increasing about 244% over the sample period. In addition, the statin drugs have been the top selling class in the U.S. during the period between 1999 to the present with total revenues of $12.5 billion dollars in 2002. The drug products in the statin class that are in the market during the sample period include Pravachol, Zocor, Lescol, Lipitor, Baycol, Mevacor, and Generic Mevacor.[8] In 2002, Lipitor and Zocor were the highest selling drugs in the world.[9]

Advertising expenditures on DTCA in this class have grown in step with the market, increasing about 298% from 59 million spent in 1996 to 175 million spent in 2002. The spending on DTCA was almost entirely for the three top sellers in the class Pravachol, Zocor, and Lipitor. These drugs accounted for 99.5% of expenditures in the class across all years. Zocor spent the most on advertising with approximately 374 million while Lipitor and Pravachol each spent about 220 million.

Another component to the marketing strategy of drug companies are the

[7] See the drug therapy section of the NCEP (2001).
[8] Other drugs have entered the class since the end of my sample in 2002.
[9] From IMS health pharmaceutical sales estimates.

marketing expenditures directed toward doctors. This includes advertising to doctors using sales representatives (often called detailing) and providing free samples of the drug products. I do not have these data for the statin drug class, but marketing toward doctors in general is about 70% of the advertising budget (See Berndt (2005)).[10] Although marketing data directed toward doctors is not included in the current study, Rosenthal et al (2003) shows that detailing is much less effective at expanding the market relative to DTCA. The elasticity of drug class demand with respect to detailing is measured between 0.017 – 0.034 compared to DTCA which they found to be about 0.10.

2.4 Analytical Model

I model the start/stop decision of individuals by applying a dynamic discrete choice model of demand. The model includes observable information of the individual, DTCA data, and controls for other factors that may affect demand over time. Most importantly, the model captures the persistence in use by including information on the individual's previous purchase decision in the model. Including the past choice is essential for measure the differential impact that DTCA has on those that have recently purchased and those that have not. However, placing the previous decision of the consumer in the model leads to a common problem faced in dynamic models - separately identifying the effect of the past decision of an individual (state dependence) from unobservable consumer specific factors affecting demand (unobserved heterogeneity).

Including the individual's previous decision in the econometric model creates an initial conditions problem because I only observe a partial history of the individual decisions. This problem arises due to correlation between the initial choice observed in the data and the unobserved heterogeneity of the individual. In the

[10] This excludes free samples whose costs are difficult to measure.

case of cholesterol drugs, it is likely that the first cholesterol check of the individual, which is unobserved in the data, will likely be correlated with all subsequent decisions regarding treatment, including the initial treatment decision observed in the data.[11] This is a problem because the correlation between the unobserved factor and the initial choice can produce inconsistent estimates. To deal with the initial conditions problem, I apply a simple dynamic model proposed from Wooldridge (2004) to control for remaining unobserved factors that may be correlated with the initial choice. In addition, I use detailed individual level information described later to reduce the number of unobserved factors that could potentially be correlated with the initial decision of the individual.

2.4.1 Econometric Model

This section formalizes the dynamic discrete-choice model described above. Individual i 's decision to purchasing a drug in period t is indicated by the binary variable y_{it} that equals 1 if the individual purchases and 0 otherwise. Her decision depends on the previous periods purchase decision y_{it-1}. I allow the effects of DTCA for those on the medication (i.e. y_{it-1} 1) and those off the medication (i.e. y_{it-1} 0) to differ. For those on the medication (off the medication) they are affected by the variable $DTCA^{On}_{t}$ ($DTCA^{OJJ}_{t}$) and their response to advertising may vary in the population a^{On}_{it} (a^{OJJ}_{it}). The common effect of factors for those on and off their medication enter the model through $j3_{it}$, while differences in effects for those that are on their medication enter through p_{it}. Finally, I assume that there is an unobserved components to a individual's decision that does not vary over time, c_i and another component that does, $r=_{it}$.

Given these components, a person on the medication uses the drug if:

[11] [1] In the case where the inital decision is actually observed in the data, the initial conditions problem does not arise. Unfortunately I do not observe the initial choice decision of the consumer, as is the problem here.

$$a_{it}^{On} \; DTCA_t^{On} + j3_{it} + p_{it} + c_i + r=_{it} > 0$$

and does not otherwise, and person off the medication uses the drug if:

$$a_{it}^{OJJ} \; DTCA_t^{OJJ} + j3_{it} + c_i + r=_{it} > 0$$

and does not otherwise. These two expressions may be combined to describe the decisions of people on or off their medication:

$$y_{it} \quad 1 \qquad ij \quad a_{it}^{OJJ} \; DTCA_t^{OJJ} \; (1 - y_{it-1}) + a_{it}^{On} \; DTCA_t^{On} \; (y_{it-1}) + j3_{it} + p_{it}(y_{it-1}) + c_i + r=_{it} > 0$$

$$y_{it} \quad 0 \qquad \text{otherwise}$$

The observed factors that affect both types of individuals may be expressed as:

$$j3_{it} \quad j3_O x_{it} + j3_1 M_t$$

The decision to use a drug depends on the individual's characteristics x_{it} and other market level factors affecting all individuals at time t denoted M_t. The difference in use for individuals on the drug may be expressed as:

$$p_{it} \quad p_O + p_1 Product_{it-1} + p_2 M_t$$

The difference in use for those on the medication may differs by a constant p_O, the product purchased in the previous period $Product_{it}$, and the market characteristics M_t. I allow the responsiveness of individuals to advertising to vary in the population by allowing a_{it}^{On} (a_{it}^{OJJ}) to depend on individual characteristics. So, for example, I may specify $a_{it}^{On} \quad a_O + a_1 x_{it}$.

I make two distributional assumptions in the above model. First, conditional on c_i, I assume that $r=_{it}$ is normally distributed which gives the usual probit probability of choosing to use a drug, if>($a^{OJJ}_{it} DTCA^{OJJ}_{t}(1 - y_{it\_1}) + a^{On}_{it} DTCA^{On}_{t}(y_{it\_1}) +$ $j3_{it} + p_{it}(y_{it-l}) + c_i$). Next, I integrate over the distribution of c_i.

Special considerations need to be made when choosing the distribution of c_i. Because of the inital conditions problem a potential bias that may arise in the model if there is correlation between $.c_i$ and the initial choice made by the individual y_{iO}. Instead of modeling the joint distribution of all of the individual's choices $(y_{iO}, y_{il}, ..., y_{iT})$ I follow Wooldridge (2004) and obtain the joint distribution of $(y_{il}, ..., y_{iT})$ conditional on y_{iO} and x_i, where x_i is the average of the individual characteristics over all time periods. In this model the density of c_i depends on both y_{iO}, $x_i$and parameters r which is expressed as $h(c_i I y_{iO}, x_i, r)$. Given the density of c_i the joint density of $(y_{il}, ..., y_{iT})$ may be expressed as:

$$j(y_{il}, ..., y_{iT} I y_{iO}, x_i, B) \qquad \int_{-00}^{r00} j(y_{il}, ..., y_{iT} I y_{iO}, z_i, c_i; j3) h(c_i I y_{iO}, x_i; \mathbf{r})$$

A convenient choice of density function for $h(c_i I y_{iO}, x_i; r)$ is $N(r_O + r_l x_i + r_2 y_{iO}, a_a)$ which implies that $c_i \; r_O + r_l x_i + r_2 y_{iO} + a_i$ where a_i v; $N(0, a_a)$. Given the above assumptions, an individual i chooses a drug in period t if

$$a^{OJJ}_{it} DTCA^{OJJ}_{t} (1 - y_{it-l}) + a^{On}_{it} DTCA^{On}_{t} (y_{it-l}) + j3_{it} + p_{it}(y_{it-l}) \; + r_O + r_l x_i + r_3 y_{iO} + a_i + r=_{it} > 0$$

This model simplifies to estimating a random coefficient probit model.

2.4.2 Identlficatlon

The model identifies both short and long term effects of advertising. The short term effects of advertising are captured directly through the effects of advertising on use in the immediate period. These short term effects are identified through correlation between the individual's start/stop choices and variation in advertising over time The long term effects of advertising enter the model indirectly through persistence in consumer use. This assumes no direct, long term effects of advertising on individual demand, so an ad seen by an individual in 1996 does not directly affect her decision to purchase in 2001.

Identification of the advertising variable may also raise some concern because it is choice variable of firms. A bias may arise if unobserved factors are correlated with the individual decisions to use a statin drug. For instance, Lipitor entered the market in 1997 which may change the perceived value of individuals seeking medication or doctors providing treatment and this may also be correlated with DTCA expenditures. A number of factors greatly reduce any potential bias from estimating the effects of the advertising variable. First, I include a flexible trend variables that differentially affect those on and off medication and allows for the presence of unobserved market level factors that shift demand over time. With the inclusion of the trend variables one can view the effects of direct-to-consumer advertising as being identified through "local" changes in advertising. Allowing these trends to differentially affect those on and off a drug accounts for other information sources that may also have different impacts on these individuals.[12] Second, the model uses detailed microeconomic data including important health conditions of individuals as well as their past choices. This significantly reduces the likelihood that there will be a common unobserved component to demand across individuals. Finally, firms have less experience with DTCA relative to other choice variables such as price or

[12] [2] E.g. A news story about the benefits of cholesterol drug treatment may have a different effect on those using the drug and those not using a drug in the same way as an advertisement.

advertising toward doctors, so firms may still be experimenting with this form of advertising over the sample. To the extent that firms experimentation is random over the period of study, the level of advertising by firms will be uncorrelated with other factors affecting mean utility.

Since I do not observe the advertising exposure on the individual, it will not be possible to distinguish response to advertising from advertising exposure. Identifying an effect on a particular group may only reflect the television viewing habits of the different populations. In any case, understanding what populations are responding to advertising is still informative about how the ads may be used to target different populations of individuals.

Finally, another effect of DTCA may be to raise the awareness of health problems. If advertising has an impact on consumer awareness, then the effects identified in this paper will be a lower bound for the full effect of DTCA. The results of one study suggest that this bias may be small for the treatment of high cholesterol. Weissman et al (2004) looks at the effect of of DTCA on diagnostic prevalence. They survey a national sample of 632 doctors that who record information on patients that initiate a discussion based on a drug advertisement. A new diagnosis was made in approximately 25% of these visits. However, for visits where the patient asks about cholesterol treatments only 3.2% of the visits resulted in a new diagnosis. One important caveat is that the study took place in 2001, near the end of the sample and after significant market growth in the cholesterol market, so it is not clear if this fraction would be higher in earlier years.[13]

[13] [3] In addition, although 3.2% seems like a small fraction, it is difficult to judge the economic importance.

2.5 Data

I combine individual panel data from the Medical Expenditure Panel Survey (MEPS) with monthly DTCA expenditure information from TNS Media Intelligence/Competitive Media Reporting (CMR) for the period 1996-2002. The MEPS selects a random sample of households and surveys all individuals in a household. It follows the individuals for two years, during which it records information on individuals over 5 rounds, where each round is approximately 4-6 months.[14] The data recorded in each round includes details on the individual's insurance, demographic characteristics, health condition, and medical expenditures. In the analysis that follows, I will define a period as a round. The MEPS study supplements the survey data by contacting the individual's medical providers and pharmacies to obtain billing information. For instance, if a patient reports purchasing Zocor from a specific pharmacy, the pharmacy is contacted to provide a payment history for all purchases of Zocor from the individual. Each year approximately 15,000 individuals enter the data so the data set is an overlapping panel. The MEPS includes out-of-pocket payment information for prescription drugs. For individuals that purchase drugs the payment information is observed so we know the price paid by the individual. Exact payment information is not observed for individuals that do not purchase prescription drugs.

The MEPS also includes detailed condition information. Individuals are asked to write about their current medical condition and health history, including when their medical problems began. For each medical event (e.g., doctor visit or prescription drug purchase), individuals are asked about the medical conditions that gave rise to the event. Professional coders take the information provided by the individual and assign one of 5 digit ICD-9 codes (International Classification of

[14] [4] Expenditures on prescription drugs are allocated to different years, so for rounds that fall into two different years, I am able to splits round into two distinct periods.

Disease Code, Ninth Revision) which describe the individual's medical condition. To protect the identity of individuals in the sample, the 5 digit ICD-9 code is aggregated into 3 digit ICD-9 codes. The 5 digit ICD-9 codes are also aggregated into 260 clinically meaningfully categories called using Clinical Classification Software. In this paper, both the 3 digit ICD-9 codes and clinical classification codes are used to describe the individuals medical condition. After reviewing risk factors mentioned in the ATP III report, and with the help of Dr. Rasmussen, I classified the 3 digit ICD-9 and clinical classification codes into the four categories: cholesterol disorders, atherosclerotic conditions, diabetes and hypertension. The only group requiring more than one code was atherosclerotic conditions. This grouping consists of various forms of heart disease, atherosclerosis, stroke or prior heart attacks. All of the problems listed above are chronic conditions, so that once an individual is observed as having the condition, he is assumed to continue to have the condition.[15]

The DTCA data provides total monthly expenditure on advertising, including expenditures across various media outlets such as television, newspaper, magazines, radio and internet. The expenditure data are adjusted to 1996 dollars using a monthly producer price index for advertising from the Bureau of Labor Statistics. The data are adjusted so that the expenditures approximate the quantity of advertising.

The direct-to-consumer advertising data are matched to the individual data based on drug names and dates. Each observation of the MEPS covers multiple months while the advertising data shows expenditures for a single month, so the mapping between individual data and the advertising expenditures data is not one-to-one.[16] The next section describes the construction of the advertising variables and other key variables used in the analysis.

[15] [5] All of these conditions are listed as priority conditions in the MEPS which means that the information on these conditions is recorded whether the individual has a medical condition or not.

[16] [6] The dates of each period are rounded to the nearest month.

2.5.1 Variables

The dependent variable $Drug_{it}$ equals one if any amount of the drug is taken in the current period and zero otherwise.[17] The variable $Prev.Drug_{it}$ is the previous value of the dependent variable for individual i ($Prev.Drug_{it}$ $Drug_{it-1}$). To account for the initial conditions problem I also include the variable $init.Drug_{it}$ which is a dummy variable indicating the initial drug choice of the individual made in the initial period 0 ($init.Drug_{it}$ $Drug_{iO}$).

I construct a separate price variables for those on and off of a drug. For both types of individuals the unit of price used is the amount paid out-of-pocket for a single daily dose of a drug. I measure the daily dose as a single tablet of the drug, which is the dosage that is typically prescribed. For both types of individuals the actual price paid in the current period is not observed, so for each type I construct a proxy for price. The construct a different proxy variable for price for the two types of users. For individuals that are on the drug, the average price paid for a tablet of statin medication in the previous period is a good proxy for the price paid in the current period. The price variable is $Drug\ Price^{On}_{it}$ is calculated by dividing the total out-of-pocket expenditures on the drug in the previous period by the quantity of tablets purchased.[18] Unfortunately I do not observe a similar proxy variable for those off the drug. Therefore, I construct the price variable $Drug\ Price^{OJJ}_{It}$ as the average price paid for a tablet by averaging the price paid across individuals that I observe purchasing. I construct a different average price for those with and without drug insurance for each year in the data.[19]

I construct different advertising variables for those on and off the medication

[17] [7] To account for stockpiling, I assume that the average daily dose for each drug is taken, and I divide the total quantity of dosages purchased by the average daily dose to determine the number of treatment days purchased. If the number of doses exceed the number of days in a round, that dosage is carried to the following round.

[18] [8] For example, if a consumer purchased 30 tablets of Lipitor and spent $5, the price variable would be $5/30 tablets=16.7 cents per tablet.

[19] [9] The price variables are adjusted to 1996 dollars using the CPI.

that correspond to the time period in which individuals make their start/stop decisions. I illustrate the construction of these variables for period 2 shown in the figure below. The figure shows two hypothetical decision periods covering the duration from March 1999 to December 1999 along with monthly advertising expenditures that fall into each period.[20] For an individual that was off the medication, their decision to start using will clearly appear in the second period. The advertising variable for an individual that is not on medication, $DTCA_{it}^{OJJ}$, is just a simple average over the second period, allowing for a one month lag in response time of the individual (i.e. Average of the months July 1999 to November 1999).[21]

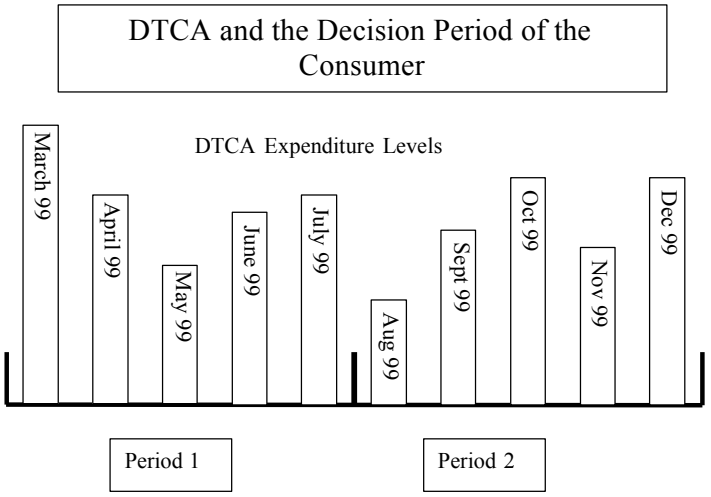

Figure 2.1

For individuals that purchased in period 1 and not in period 2, it is not clear if they actually stopped in period 1 or period 2. However, it is unlikely that the decision to stop was made later in period 2 because if this were the case we would

[20] [0] I round the day of the period to the nearest month to determine the expenditure data applicable to a particular period.

[21] [1] The lag accounts for the response time to schedule an appointment, be prescribed medication, and purcahse a drug.

likely see purchases earlier in that period. Therefore, the advertising variable for those on the medication is lagged to capture the importance of advertising in the previous period. I construct the advertising variable for those on the medication, $DTCA_{it}^{On}$, to reflect the timing of the stop decision by averaging advertising expenditures over a 6 month period starting 6 months prior to the end of period 2 (i.e. July 99-February 99).

Although the advertising data is averaged across a number of months, the average varies across the individuals in the sample because the beginning and end dates of the periods are not the same across individuals. Therefore, there is considerable variation in the advertising variable in the population.

A description of the remaining individual variables, trend variables and other control variables are discussed in a variable appendix at the end of the paper.

2.5.2 Sample

The sample used in this paper is inclusive of a large fraction of the individuals in the MEPS survey. The sample includes individuals that list a cholesterol condition and those that do not because awareness of one's own condition may vary in the population and some other combination of risk factors may cause indivduals to use a statin drug.[22]

A number of factors limit the number of observations used in this study. First, I exclude all individuals who are 30 or under because cholesterol levels tend to increase with age and cholesterol drugs are rarely taken by the population in this age group.[23] Second, the first period of every individual is dropped from the analysis because I do not observe the choice made prior to the initial period in the sample. Finally, the data are adjusted so that all periods are greater than 2 months

[22] [2] This sample constrasts with sample of only informed consumers studied in chapter 1 of this dissertation. Other risk factors include diabtes, hypertension, age, family history and smoking.

[23] [3] The data shows that only 0.08% of those between the ages of 20 and 30 purchase a statin drug.

in length. If I observe a period that is less than two months in length I combine the information from this period with an adjacent period for that individual.[24] This last restriction ensures that an individual's decision to stop purchasing a drug is not mistaken for unobserved inventory or the individual forgetting to take the drug for a week.[25] After selecting this sample, I observe a total of 59, 922 individuals with 221, 120 observations.[26]

2.5.3 Descriptive Statistics

Figure 1 shows the total monthly expenditures on DTCA for the statin class split into categories of expenditure devoted to television and non-television advertising (i.e. radio, newspapers and magazines).[27] The table shows considerable growth in advertising and substantial variation in the level of advertising over this period that should help in identifying advertising effects. The figure also shows the change in the marketing mix after the FDA rule change. Before the rule change the fraction of DTCA dollars in the statin class devoted to television advertising was 13.0%, but after the rule change the fraction rose to 53.2%.

The growth in the number of users in the market was considerable. Table 2.1 shows the population of individuals over the age of 30 in the United States and the number of those individuals that use statin drugs. The average growth rate in the number of users over the period was a rapid 23%. In addition, the population of individuals that purchase a statin at least once was substantial relative to the total population, with approximately 13.4% of the population over the age of 30 using a

[24] [4] If there are two adjacent periods I combine the data with the smaller length period. The update involves changing the dates of the sample period, adjusting the advertising variable, and accounting for the purchases made in the two periods.

[25] [5] I chose two months because individuals typically purchase 30 day supplies of a drug and a two month window allows for an enitre months purchase to be missing without affecting the model.

[26] [6] The population of consumers analyzed in the results section of this paper differs slightly from the sample analyzed in this section because the model includes lagged advertising expenditures and I do not observe the lagged advertising expenditures for some of the observations in 1996, these observations are excluded from the regression analysis.

[27] [7] The advertising is adjusted to 1996 dollars using the PPI for overall media advertising.

drug at some point in 2002.

The growth in the use of drugs consists of new users coming into the market and those on the medication continuing to use the drugs. I observe about 15,000 periods in which a drug is purchased. Of all purchases, about 75% of them consist of individuals that purchased in the previous period, and the remaining 25% are new users. Of those individuals that used a drug in the previous period about 80% of them use the drug in the following period and the remaining 20% do not.

There are a variety of purchase patterns observed in the data. Table 2.2 shows the various patterns for the 6,125 individuals observed purchasing statin drugs at some point in the data. The first column of the table describes the start/stop pattern observed, the second column shows the number that fall into that category, and the last column shows that categories fraction of the 6,125 individuals. About 31% of the sample are observed purchasing a statin drug in every period of the data and 27% are observed starting treatment and not stopping. These two groups represent the compliant population which make up a majority of the data. About 22% of the sample consists of people that are observed taking the drug and then stopping. The remaining 20% of the sample consists of people who stop and restart or have multiple stops and starts.

Table 2.3 shows some descriptive statistics for the main variables used to explain individual start/stop decisions.[28] The average price faced by potential new users is higher on average than the price faced by previous users. The variation in price measured using the standard deviation is much greater for the previous user than for the new user. This is due to the price variable for new users being calculated as an average over the population.

Even though the advertising variables for those on and off medication are constructed differently, the distributional properties of these variables are very similar.

[28] [8] These data are not weighted by the population weights, so they are not nationally representative.

For both variables there is considerable dispersion in the amount of advertising that individuals are exposed to in the data with a standard deviation in the advertising variable of nearly 5 million dollars.

There are a few additional things to point out in table 2.3. First, it was noted before that a number of studies focus on privately insured individuals only, but we see here that a substantial fraction of the sample is not covered by health insurance (12.2%) and an even larger fraction is not covered by drug insurance (32.2%). Second, there is a sizable 8.9% of individuals reporting a cholesterol disorder. Those that report having either a cholesterol disorder or some other atherosclerotic disorder make up an even larger fraction of the data covering about 13% of the sample. Individuals with one of these two conditions make up 85% of the observed purchases of statin drugs. The remaining purchases are either by individuals with some other combination of risk factors or by individuals that are unaware of their condition.

2.6 Main Results

Before turning to the estimates of the full model and analyzing the heterogeneous effects of DTCA, I first separately analyze the population of individuals that were not on a medication in the previous period and those that were. These preliminary results allow for some additional robustness checks of these data.

2.6.1 Population Not On Medication

Table 2.4.1 shows probit regression for the population of individuals that were not on a medication. The first column of table 2.4.1 shows the set of variables used in this analysis. For each set of estimates, the first column shows the coefficient values and the second shows the asy-z statistics. Most of the estimates in model 1 are as expected. The effect of advertising is positive and statistically significant.

Individuals respond negative to price, those with health insurance are more likely to purchase prescription drugs and all the risk factors contribute positively and significantly to an individual purchasing a statin drug.

A key problem with the first model is that one cannot separate the effect of advertising in the first model from a general trend in the market that may be caused by factors other than DTCA. The second model includes a single trend variable, and I find a significant and positive trend effect over time and the coefficient on advertising drops considerably. To allow for more flexibility in the market trend I include higher order polynomials of the trend value in the model. I find significant improvement in the fit of the model, and the statistical significance of the advertising variable increases. Throughout the remainder of the analysis I include a fifth order polynomial time trend.[29]

One may be concerned with lumping individuals that are deciding to start with individuals that are deciding whether to restart (i.e. An individual observed purchasing, stopping, and then restarting). It may be that one group is responding to advertising, while the other is not. To see if this is the case, I run the probit regression seperately for these two groups. I find that advertising has a significant and positive effect on both of these groups.

2.6.2 Population On Medication

Table 2.4.2 shows four probit regressions for individuals that recently purchased a statin drug. The first three models included here are parallel to those in table 2.4.1. First I exclude a trend, then add a single trend, and next a higher order polynomial trend. Qualitatively, the findings are identical to those in the last section, which leads me to the conclusion that including higher order polynomial

[29] The results are nearly identical if the model is estimated with either a 4th or 6th order poly- nomial trend.

trend seems important for capturing the demand effects of DTCA.[30] The signs and significance of many of the other variables are similar to the results from the previous model. One difference is that the price variable proxied for by the price paid by the individual in the previous period is very precisely estimated in this model and suggests that the past price may be a good proxy for the current price.

Examining this population helps check for a potentially serious reporting bias that could influence the results of this paper. A reporting bias could arise if individuals are more likely to report a drug purchase on the survey because they see an ad reminding them to. This would cause an upward bias on the advertising coefficient because consumers would be more likely to report using the drug when expenditures are high. Although the MEPS also surveys the individual's pharmacy to limit this type of bias, it does not ensure that the bias is nonexistent.

One way to check for a reporting bias is to look at how current advertising affects demand for those on medication. As discussed in the variables section above, there is good reason to believe that current advertising may have less of an effect on those that are on medication because if they decide to stop taking a drug, the advertising (or lack of advertising) influencing this decision is likely to occur in the previous period or early in the current period. However, if there is a reporting bias present then there may be a stronger correlation between advertising in the current period and the individual reporting a purchase. Model 4 shows a probit using the same current advertising variable as is used for those not on a drug. I find that the advertising variable lacks statistical significance and the magnitude of the coefficient also suggests economic insignificance, which provides some additional evidence that this type of reporting bias is not present in these data.[31]

[30] Similar to the previous analysis, excluding a trend I find advertising to have a positive and significant effect on demand; with a single trend significance falls considerable and the trend is increasing; adding a more flexible polynomial trend I find advertising is again positive and statis- tically significant. Also similar to the previous analysis this result is robust to the order of the polynomial trend. Both 4th and 6th order polynomials give similar results.

[31] The result is the same with no trend variables. I also get the same result when using current

I also use the population of those on medication to check for the appropriate number of months to lag the DTCA variable. Using this model I find that a six month lag works better than using fewer lags or adding additional lags and this is consistent with the assumption that individuals make their stop decision in the previous period or early in the current period.[32]

2.6.3 Full Model

The main estimation results are shown in table 2.5. I begin by analyzing model 1 from this table. I find that advertising has a significant and positive effect on both those on and off the drug. All the health conditions, age and sex are positive and highly significant. Health insurance has a positive effect and price negatively affects both types of individuals.[33]

Model 1 also indicates that there are dynamic effects in the drug choice decision of individuals because the coefficient on past use is highly significant. To evaluate the relative importance of past use, I calculate marginal effects for the average person that is on a drug. The marginal effect of purchasing a drug in the previous period is 32% (0.029). While this effect is important it is relatively less important than the whether the consumer indicates having a cholesterol problem which has a marginal effect of 73% (0.010). The effect of having an atherosclerotic disorder is also relatively large with a marginal effect of 17.3% (0.008). Therefore, state dependence seems to plays a role, but it is not necessarily more important than the individual's health conditions.

Another interesting result in these estimates is the effect of price on individual

advertising in the full model in the next section.

[32] [2] However, one concern with using lagged advertising dollars is that they may only be affecting individuals that just started their medication, and not those that have been using the drug over multiple periods. To check this I run a the probit model on those that have purchased over two periods. The number of observations drop considerably along with the significance of the coefficient, but the magnitude of the coefficient remains nearly the same.

[33] [3] I used a likelihood test to check for positive significance of past use in the second model because past use enters the second model nonlinearly.

demand. I focus the price effects for those that are on medication because the proxy variable for price seems closer to the true price faced by consumers. For those consumers that were on a drug, I find the price elasticity of demand is -0.026. This contrasts with the elasticity of demand found in the RAND Health Insurance Experiment for overall drug expenditures of -0.27,(See Newhouse (1993)) and the typical range in the literature is between -0.20 to -.35. There are a number of explanations for this lower elasticity. First, an elasticity for expenditures does not correspond to an elasticity of use because one may shift expenditures while still taking medication by shifting to cheaper alternatives.[34] Second, one could reduce quantity or stop the use of other drugs that may be viewed as less essential than cholesterol medication.

The factors that enter the distribution of c_i are also important. Estimates show that the inclusion of individual-specific random effect is highly significant with a random effect of 1.19 implying a correlation of p .59 (0.011) across periods. The inclusion of the initial choice is positive and highly significant. I also include mean health insurance as a component and find it to be highly significant, although it limits the models ability to identify the health insurance variable separately.

Model 2 differs from model 1 by the inclusion of trend variables. Including the trend variables shift both the magnitude and the significance of the advertising coefficients, suggesting that these unobserved factors captured by the inclusion of the trend variable may be correlated with the advertising and may bias estimates of the advertising variables.[35]

Model 3 is included as a robustness check. It differs from the second model because it includes a number of additional terms entering c_i as mean values of some

[34] [4] E.g. For statins, someone could shift from Zocor, a drug that is typically more expensive, to Baycol, a drug that is typically less expensive without stopping use. Also, pill splitting is a common practice that often lowers expenditures.

[35] [5] Alternatively, one must be careful in including trend variables because advertising is identified through variation over time. Therefore, multicollinearity with the trend variables may limit the models ability to identify advertising effects.

explanatory variables.. These variables include the mean of advertising, age, drug insurance, family income, and health insurance. I check to see if these variables capture any additional unobserved heterogeneity which may be important in precisely identifying state dependence. The only value that appears significant at the 95% level is mean health insurance, indicating that those that tend to have health insurance also tend to receive higher draws of c_i.

The mean advertising variable included in model 3 is an important check against a potential endogeneity problem that could arise from companies choosing when and where to advertise. Advertisers may be targeting individuals with particular values of c_i, and if this were the case we may expect the mean level of advertising experienced by a individual to be correlated with use. Although the coefficient is positive it is not significant, and the other advertising variables change little when it is excluded from the model. For the remainder of the analysis I focus on the estimates from the second specification.[36]

Now I turn to analyzing the effects of DTCA on demand. I measure the effect of DTCA through market elasticities with respect to changes in advertising levels. To calculate these elasticities I first choose a single cross section of individuals from each year of the sample. I calculate market demand Q in each cross sections by applying population weights to the individuals in the sample. I compute the market elasticities for a single cross section in the immediate period using the simple formula:

$$\frac{\%/:)Q}{\%/:)DT\,CA} \qquad \frac{\frac{(Q(DT\,CA*l.l)-Q(DT\,CA))}{Q(DTCA)}}{.10}$$

There is also a dynamic effect from a change in advertising that acts through

[36] [6] I perform a number of additional robustness checks on model 2. I estimate model 2 with both 4th and 6th order polynomial trends and get similar results. Estimating the model with alternative functional forms on DTCA variables including log(DTCA) and DTCA interacted with the length of the time period.

state dependence in the model. I analyze how this state dependence carries through to the following periods by looking at how a one period increase in DTCA affects market demand in subsequent periods. In other words, I introduce a dose of advertising in one period and follow that effect through time by calculating elasticities in the following periods.

To calculate elasticities in the current and future periods I simulate purchase histories for 4 periods for every individual in the sample. Over these 4 periods I hold all characteristics of the consumer and the market to be the same values as in the first period, and only allow the consumers choice and the state dependent variable to change in each of the following periods. In each of the following periods I calculate an elasticity from a change in advertising in period 1. For example the elasticity for the following period would be:

$$\frac{\%/:)Q_{t+1}}{\%/:)DT\,CA_t} \qquad \frac{(Q_{t+1}(DT\,CA_t*1.1)-Q_{t+1}(DT\,CA))}{Q_{t+1}(DT\,CA)} \qquad .10$$

I compute 200 simulated market elasticities based on Model 2 results. Table 2.6 shows the results from these calculations. Looking across the columns, I show the effect of advertising in the initial period's demand and the effect of advertising on demand in the following periods. The rows of the table show the group of individuals that I'm averaging over. For each period and each group of individuals I show the mean and standard deviation of the market elasticity across the 200 simulated elasticities The first three rows of Table 2.6 show the elasticity calculations overall, for those on the drug, and those not on a drug. The overall effect on market expansion in the first period is 0.107. This result is very similar to the expansion results found by Rosenthal et al (2003) that calculated an elasticity from DTCA of about 0.10 looking across multiple drugs. However, the static effect in period 1 is just a portion of the overall demand effect. I find that the demand effect in the second period is also significant with an elasticity of 0.021. The demand effect in

the third period is nearly significant, but the economic magnitude is quite small.

Comparing the effects for individuals that are on and off the drug, I find that the elasticity of advertising for individuals not on a drug is higher in the current period compared to later periods. In period 1 the market elasticity for those not on a drug is 0.158, and the elasticity is 0.086 for individuals that purchased a drug in the last period. Below these results the table shows the overall elasticity in each period calculated for each year. The individual year estimates are less precisely estimated than the overall calculations, but they show a pattern similar to the overall demand effect.

I also computed these elasticities based on model 1 estimates which are shown at the bottom of table 2.6. In these results I find the overall elasticity in period 1 to be about 0.109, the elasticity for consumers not on a drug is 0.24, and the elasticity for those on a drug is 0.04. I found a similar declining pattern in the effect over time. The overall effects are similar in both models, but relative to model 2, the results from model 1 seem to overstate the effects for consumers not on a drug and understate effects for consumer that are on a drug.

The results from both model 2 and model 1 are qualitatively the same. The effect of DTCA seems to primarily affect those not on a drug, which is consistent with DTCA primarily being informative. The positive and significant effect on those that are on a drug suggests that either the DTCA is new information for these consumers, implying that the consumers are not fully informed orr that DTCA is somehow persuasive.

While the dynamic effect is present, it does not appear large relative to the current effects. Therefore, there is some incentive for firms to advertise earlier rather than later because of the additional demand in the following period, but there is also incentive to continue advertising after the initial period. The importance of health conditions on individual demand suggests that modeling the effect of advertising on

awareness may be important. Morever, if consumers remain aware of their health condition in the future, an affect on consumer awareness could have a lasting impact on prescription drug use and which is not captured in these estimates.

2.6.4 Other Heterogenous Factors

This section analyzes other factors that may cause heterogeneous responses to DTCA. I analyze the different effects based on characteristics of the individual, effects of the FDA rule change and consumer responses to different product advertisements.

The effects of the FDA rule change and television advertising may be difficult to identify with the current model because they are identified through variation in advertising over time. With only 7 years of data and for one product class it may be difficult to separately identify additional factors affecting responsiveness to DTCA over time. These results should be viewed as preliminary.

This identification problem is not as serious when looking at effects of advertising on different types of individuals because individual characteristics vary in the cross section of the data. Identification of these effects are based on individuals with different characteristics responding differently or similarly to the same levels of advertising.

Individual Heterogeneity

I estimate alternative models to see if I can capture other heterogeneous effects of DTCA for different types of consumers. Table 2.7 shows just the coefficients on DTCA and interactions with DTCA with individual characteristics. In the first model I combine the DTCA variables into one variable[37] and interact it with the individual characteristics, essentially restricting the effect of DTCA to be the same

[37] $DTCA_{it} = DTCA_{it}^{On} + DTCA_{it}^{Off}$.

for those on and off the medication. The variables that I interact are medical insurance, price of the drug, age, cholesterol disorder, education and income.[38] I interpret the interaction with the cholesterol disorder variable as an indicator of both a condition, but also as an indicator of the individual's awareness of her condition. Since doctors prescribe medicines for their patients, it may be the case that patients are not always aware of why they may be taking a medication.

The only variables that are statistically significant are education and cholesterol disorder, while the coefficient on medical insurance is nearly significant. If those with less education, those unaware of having a condition, and those without medical insurance are less informed populations then these results are also consistent with DTCA having an informative effect on consumer demand.

The significant effect on education is particularly interesting as it lends support to a theory by Michael Grossman (1972 a, b) relating demand, health and education. The theory is that better educated people are more efficient producers of health as they may know better how to use existing medical inputs. The full model results in table 2.5 showed a positive effect of education on use, but interacting education and DTCA in table 2.7 shows that the education variable is insignificant and that the effect of education with the interaction of DTCA is significant. This result implies that more educated individuals are less responsive to DTCA. The empirical result presented here is not a direct test of Grossman's theory, but it suggests that advertising is less likely to be new information for more educated individuals which is consistent with them being more knowledgeable about medical inputs.

The second model in table 2.7 focuses more closely on the price of the drug and medical insurance. In this specification I allow for differential effects for those on and off the drug by interacting the different advertising variables with price and medical insurance. These estimates show that individuals with medical insurance

[38] [8] For the variables age, education and income I subtracted the median level in the population before interacting them with DTCA. (i.e. (age-50), (education-12), and (income-40)).

are particularly responsive to advertising after they have purchased a drug. The fact that medical insurance has an effect on responsiveness to DTCA but price does not, provides additional support for DTCA being informative rather than changing consumer's willingness to pay for statin drugs.

As mentioned previously, I do not observe the exposure rates to different populations, so instead of representing responsiveness to advertising, it may actually be picking up the TV viewing habits of these populations. This is an important caveat for the interpreting the results in this section. An alternative interpretation to the given results is that those with more education, health insurance, and those reporting cholesterol problems have less exposure to advertising. Evidence against the alternative interpretation is that one might also expect that income and age would be important covariates to explain exposure, but they appear insignificant in these regressions.

FDA Ruling & Media-Type Effects

Table 2.8 looks at the effects of television and non-television advertising expenditures as well as changes in the effects of DTCA after the FDA ruling. I construct television and non-television advertising variables that average the expenditure within each type of media over the relevant period. I find that television and non-television advertising have similar coefficients for those that are not on a drug, but non-television advertising is statistically insignificant. I find that individuals that are on a drug respond more to non-television advertising. As suggested in Wosinska (2004) the side effects mentioned in television advertisements may be more noticeable than side effects listed in small print in newspaper and magazine advertising, and this could explain the relative effectiveness of print advertising versus television advertising at keeping consumers in the market.

Next, I construct an FDA rule change variable which is an indicator of 1

if the individual's period begins after the FDA rule change. I find that the FDA change had a statistically insignificant effect on both types of individuals. Although the result show a negative effect of the rule change for those not on a drug, overall I found this result quite sensitive to the time period I select as the starting point of the FDA rule change. The estimates sensitivity may be due to confounding effects from changes in the FDA ruling, Lipitor's entry, and simultaneous shifts in the type of advertising used.

Product Effects

Table 2.9 examines how advertising of specific product affects individual responsiveness to demand. In particular, how individuals that are on medication respond to the advertising of the product they are taking compared to the advertising for other products. Since this is not a differentiated product demand model I cannot tell whether individuals are switching brands as a result of the advertising, but I can see if they continue purchasing some product in the statin class. I decompose the advertising expenditure for those that are on medication into expenditures that are on one's own product and on other products. Model 1 shows the effects are positive and significant for both own and other product advertising. Using a Wald test, I cannot reject the hypothesis that these coefficients are the same.

I look at how advertisements for particular products affect individuals that are using the product. I find that Zocor and Pravachol advertising has a positive and significant effect on customers purchasing a drug in the statin class, while Lipitor's effect on its own customers is insignificant. This result could potentially be explained by the relative proportion of television and non-television advertising used by the different companies. Lipitor is the heaviest user of television advertising relative to the other two companies, which may explain the smaller effect on retention for Lipitor users. Wosinska (2004) finds a related result. Wosinska (2004) finds

Lipitor advertising has a negative effect on compliance over some periods. She argues that initial television advertising by Lipitor may have had a "shock" effect on a large number of individuals already taking the drug that learn about the side-effects of the drug for the first time. However, her results are also preliminary.

2.7 Conclusion

This paper analyzed the effects of DTCA on market expansion for anti-cholesterol drugs in the statin class. I find that higher DTCA expenditures are correlated with more individuals starting medication and fewer stopping. The elasticity of demand from an increase in DTCA is 0.107. I also found that the population of individuals on a drug was more responsive than the population not on any drug. The estimates also suggest a dynamic component to consumer demand with a 10% increasing in advertising in the current period causing a 0.2% increase in demand four months later. This paper also examines other heterogeneous factors that affect demand. I find that those with less education, those that are unaware of their health condition, and those without health insurance are more responsive to DTCA. The results from this paper are consistent with advertising having the greatest effect on populations that are typically thought of as being less informed about the need for prescription drugs.

There are a number of important areas for future empirical and theoretical research. Empirically, an important effect of DTCA may be the effect of individuals discovering that they have a health condition. If the discovery effect is important this would suggest that my estimates are only a lower bound for the full effects of DTCA, and additional work on condition discovery is needed to capture the full effect of advertising.

Another area of empirical research is to apply a differentiated product demand model that may help identify DTCA effects. A differentiated product demand

model would help separate many factors that are actually observed in the data (i.e. products, market price and other characteristics), but assumed to be unobserved in the current model. This may be especially important for identifying the expansion effects of particular product advertising and determining the effectiveness of television/non-television advertising that is difficult to identify solely through variation in advertising over time.

Determining the optimal amount of DTCA is an important theoretical question for both firms perspective and policy makers. Firms may care when and how much advertising to use in order to maximize profitability. However, policy makers may want to know if the amount of DTCA being supplied in a competitive market is under or over the amount that is needed to optimize consumer welfare. The dynamic component of consumer demand in prescription drug markets makes this a challenging theoretical question.

2.8 Data Appendix

Individual i's state of health in period t is described by four dummy variables: CH_{it} for a cholesterol disorder, HD_{it} for atherosclerotic conditions, DB_{it} for diabetes, and HYP_{it} for hypertension. Since cholesterol levels tend to increase with age, and men are at a higher risk of heart disease at a younger age, I also include the variable Age_{it} and an indicator for $Male_i$.[39] Individual i's family income in period t is measured in thousands of 1996 dollars is inc_{it}(000s). Finally, the individuals education is included in the model as the number of years of education, $Educ.Yrs_{it}$.

I use binary variables for insurance coverage. The variable $Medins_{it}$ is equal to 1 if individual i has medical insurance in period t and zero otherwise. Medical insurance coverage typically covers doctor office visits and other services, which

[39] Although one might think of including race, current treatment guidelines specified in NCEP (2001) conclude that treatment should not change by race.

makes it more likely that insured individuals will obtain statin drugs and maintain treatment, even when they do not have prescription drug insurance. Individuals on private plans, Medicaid, Medicare, or other public insurance plans are classified as medically insured. I also include individuals with prescription drug insurance coverage because it is rare for individuals with drug insurance not to have medical insurance. I also distinguish between these insurance categories and the two large public health insurance programs in the U.S - Medicaid and Medicare. I include dummy variables for $Medicaid_{it}$ and $Medicare_{it}$.

In some instances rather than use the constructed price described above, I use an indicator variable $Drugins_{it}$ that is equal to 1 if the individual i has drug insurance in period t and zero otherwise. An individual is classified as having prescription drug coverage if she has a private prescription drug insurance or is on Medicaid. This definition of drug coverage should account for nearly all individuals with drug insurance. According to Health, United States (2005) [40], in 2002, 30% of drug expenditures in the United States are paid out-of-pocket, while private insurance and Medicaid paid nearly all the remaining expenditures. Private insurers and Medicaid accounted for 48% and 18% of drug expenditures, respectively. The remaining 2% of expenditures were covered by Medicare. To account for the possibility of misreporting by consumers, I use prescription drug expenditure information provided by the MEPS to mark individuals as covered if a third party pays for a significant amount of their drug coverage for the year. I broaden the definition of those with prescription drug insurance by counting individuals as insured if their expenditures on prescription drugs are over $200 a year and over 70% of their expenditures are covered by another party.[41] To check the validity of the prescription drug insurance variable, I looked at payments made by consumers in the sample.

[40] See table 119

[41] The $200 is total expenditures including statin drugs and all other types of drugs purchased for a given year.

The average person with private prescription drug coverage only pays 34.5% out-of-pocket, and the typical person on Medicaid pays approximately 31.5%. Using my definition of drug coverage, I find that those with prescription drug coverage pay 33.3% out-of-pocket, while those that have no prescription drug insurance pay 84.9% out-of-pocket. The fact that people without coverage do not pay the full out-of-pocket price suggests that people are using alternative public sources of coverage such as neighborhood clinics or State programs.

I use a trend variable $Trend_{it}$ which is a continuous measure of time in years or fraction of years between the end date of the period and 1/1/1996.[42] I include both a linear trend and higher order polynomial values of the trend variable. I also control for seasonal variation in the model by including a seasonal trend variable $eason_{it}$ starting at 0 in the beginning of the year and ending at 1 at the end of the year.[43] I control for the variation in the length of the period by include a time variable $Time_{it}$ which is the number of days in the period measured in 30 day periods. The side-effects and other product specific characteristics of the drug taken by a consumer in the previous period may affect her choice in the following period. I use the following product dummy variables that are indicators of the drug choice in the previous period.: $Lipitor_{it}$, $Zocor_{it}$, $Pravachol_{it}$, $Mevacor_{it}$, $Gen.Mevacor_{it}$, $Lescol_{it}$. In the above specifications $Zocor_{it}$ is left out.

[42] 2 For example, for a period ending 7/1/1996 the variable would equal 0.5.
[43] 3 Using month dummies gives similar results.

2.9 Tables & Figures

Table 2.1: **Market Expansion of Statin Drug Market**

Year	Tot. Pop. Over Age 30 (in Millions)	Pop. Over 30 Used Statins (in Millions)*	% Pop. Over 30 Using Statins	Growth Rate
1996	148	6.4	4.3%	•
1997	151	8.4	5.6%	32.5%
1998	152	11.0	7.2%	30.5%
1999	155	12.8	8.3%	16.4%
2000	156	15.9	10.2%	24.2%
2001	161	19.2	11.9%	20.8%
2002	164	21.9	13.4%	14.1%

Notes:

Number are estimated using the MEPS data.

An individual is counted as using statins if they purchase once in the year.

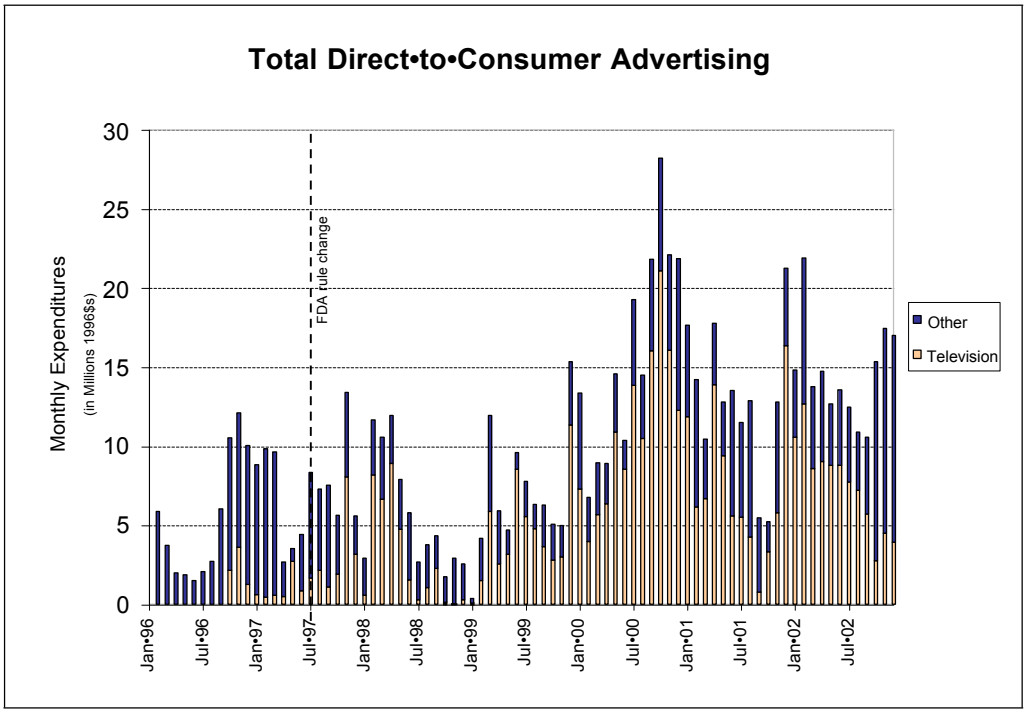

Figure 2.2

Table 2.2: **Individual Purchasing Patterns**

# Individuals In Data:	59,922
# Individuals that Use a Statin	6,125

Purchasing Pattern	# Individuals W/ Pattern	Percent of Total
Always On Drug	1,901	31.04%
Started Drug & Stayed On Drug	1,644	26.84%
Was on Drug and Stopped	714	11.66%
Started & Stopped	632	10.32%
Stopped & Re•started	734	11.98%
Other (Multiple Begin & Ends)	500	8.16%

Table 2.3: **Summary Statistics**

# Individuals	59,922
# Observations	221,120

Variable	Mean	10th percentile	Median	90th percentile	SD
Price New	1.05	0.63	0.88	1.90	0.56
Price Prev.	1.14	0.05	0.58	3.10	1.18
DTCA Off Med.*	10.33	4.69	9.57	16.40	4.99
DTCA On Med.*	10.07	4.47	9.15	14.96	4.53
Age	51.9	34	49	74	14.7
Education (# Years)	12.3	8	12	16	3.4
Family Income (000s)**	$48.50	$9.78	$39.32	$96.86	$39.40
Male	45.8%				
Medical Insuance	87.7%				
Drug Insurance	67.8%				
Medicare	24.0%				
Medicaid	9.3%				
CH (Cholesterol)	8.9%				
HD (Atherosclerotic)	8.4%				
DB (Diabetes)	8.3%				
HYP (Hypertension)	21.6%				
Time (30 Day Periods)	4.65	2.60	4.53	6.73	1.59

* Deflated to 1996$s using monthly producer price index for advertising from the BLS

** Deflated to 1996$s using the CPI

Table 2.4.1: **Probits for those that were not on a drug**

	Model 1		Model 2		Model 3	
	Coef.	Asy. Z	Coef.	Asy. Z	Coef.	Asy. Z
DTCA Off	**0.020**	**(9.72)**	**0.004**	**(1.65)**	**0.008**	**(2.60)**
Price Off	•0.065	•(2.67)	•0.094	•(3.83)	•0.085	•(3.42)
Health Insurance	0.249	(4.46)	0.221	(3.93)	0.229	(4.10)
Medicaid	•0.025	•(0.68)	•0.037	•(1.02)	•0.031	•(0.84)
Medicare	0.059	(1.65)	0.077	(2.14)	0.076	(2.11)
Family Income (000s)	0.000	(0.72)	0.000	(0.49)	0.000	(0.48)
Education Years	0.008	(2.37)	0.008	(2.35)	0.008	(2.45)
Age	0.101	(15.91)	0.102	(15.92)	0.102	(15.93)
Age^2	•0.001	•(13.72)	•0.001	•(13.73)	•0.001	•(13.76)
CH	1.785	(81.34)	1.779	(80.79)	1.781	(80.71)
HD	0.524	(18.27)	0.532	(18.40)	0.534	(18.45)
DB	0.232	(8.05)	0.230	(7.94)	0.230	(7.95)
HYP	0.164	(7.28)	0.161	(7.12)	0.161	(7.13)
Male	0.056	(2.75)	0.054	(2.67)	0.054	(2.63)
Day	•0.360	•(0.82)	•0.232	•(0.54)	•0.283	•(0.66)
Day^2	2.018	(2.12)	1.588	(1.69)	1.630	(1.74)
Day^3	•1.738	•(2.99)	•1.472	•(2.55)	•1.456	•(2.52)
Time	0.380	(3.21)	0.303	(2.55)	0.326	(2.73)
Time^2	•0.056	•(2.48)	•0.046	•(2.04)	•0.049	•(2.16)
Time^3	0.003	(2.26)	0.003	(1.99)	0.003	(2.08)
Trend			0.063	(9.31)	•1.181	•(1.42)
Trend^2					0.845	(1.64)
Trend^3					•0.241	•(1.66)
Trend^4					0.031	(1.61)
Trend^5					•0.001	•(1.55)
Trend^6						
Constant	•7.251	•(25.91)	•7.134	•(25.39)	•6.669	•(12.43)
Likelihood Function	•11,191		•11,140		•11,131	
# Individuals	57,245		57,245		57,245	
# Obs.	194,761		194,761		194,761	

Table 2.4.2: **Probits for those that were on a drug**

	Model 1		Model 2		Model 3		Model 4	
	Coef.	Asy. Z	Coef.	Asy. Z	Coef.	Asy. Z	Coef.	Asy. Z
DTCA On	**0.008**	**(2.49)**	**0.005**	**(1.01)**	**0.014**	**(2.38)**	**•0.001**	**•(0.19)**
Price On	•0.057	•(5.03)	•0.057	•(5.05)	•0.058	•(5.13)	•0.058	•(5.12)
Health Insurance	0.336	(3.85)	0.335	(3.84)	0.330	(3.79)	0.331	(3.79)
Medicaid	•0.063	•(1.38)	•0.063	•(1.38)	•0.067	•(1.48)	•0.066	•(1.45)
Medicare	0.001	(0.03)	0.002	(0.04)	0.005	(0.12)	0.005	(0.12)
Family Income (000s)	0.001	(1.87)	0.001	(1.86)	0.001	(1.78)	0.001	(1.77)
Education Years	0.010	(2.21)	0.010	(2.23)	0.010	(2.22)	0.010	(2.26)
Age	0.039	(3.95)	0.040	(3.98)	0.039	(3.92)	0.039	(3.94)
Age^2	0.000	•(3.60)	0.000	•(3.63)	0.000	•(3.58)	0.000	•(3.60)
Had CH	0.194	(6.74)	0.194	(6.75)	0.193	(6.68)	0.192	(6.67)
HD	0.116	(3.96)	0.116	(3.99)	0.117	(4.02)	0.117	(3.99)
DB	•0.016	•(0.51)	•0.016	•(0.52)	•0.016	•(0.50)	•0.015	•(0.48)
HYP	0.149	(5.60)	0.148	(5.57)	0.150	(5.64)	0.149	(5.60)
Male	0.048	(1.75)	0.047	(1.73)	0.050	(1.83)	0.051	(1.85)
Day	•1.826	•(2.97)	•1.867	•(3.03)	•2.073	•(3.35)	•2.184	•(3.52)
Day^2	4.976	(3.62)	5.107	(3.69)	5.555	(4.00)	5.984	(4.30)
Day^3	•3.241	•(3.81)	•3.337	•(3.89)	•3.653	•(4.23)	•3.970	•(4.61)
Time	0.841	(5.17)	0.836	(5.13)	0.860	(5.23)	0.844	(5.13)
Time^2	•0.130	•(3.94)	•0.129	•(3.92)	•0.135	•(4.06)	•0.132	•(3.97)
Time^3	0.007	(3.23)	0.007	(3.22)	0.007	(3.36)	0.007	(3.29)
Lipitor	0.092	(2.82)	0.089	(2.71)	0.097	(2.93)	0.097	(2.95)
Baycol	•0.230	•(3.03)	•0.229	•(3.01)	•0.188	•(2.44)	•0.178	•(2.33)
Generic Mevacor	0.108	(0.76)	0.099	(0.70)	0.036	(0.25)	0.036	(0.25)
Mevacor	0.037	(0.64)	0.043	(0.73)	0.039	(0.67)	0.038	(0.65)
Pravachol	0.034	(0.86)	0.036	(0.89)	0.033	(0.83)	0.034	(0.84)
Lescol	0.046	(0.81)	0.050	(0.87)	0.041	(0.70)	0.041	(0.71)
Trend			0.010	(0.79)	•2.736	•(2.15)	•1.222	•(0.97)
Trend^2					1.519	(1.97)	0.616	(0.78)
Trend^3					•0.384	•(1.80)	•0.142	•(0.63)
Trend^4					0.044	(1.63)	0.015	(0.51)
Trend^5					•0.002	•(1.44)	•0.001	•(0.39)
Trend^6								
Constant	•2.899	•(7.02)	•2.904	•(7.03)	•1.111	•(1.35)	•1.904	•2.38
Likelihood Function	•6,649		•6,648		•6,636		•6,639	
# Individuals	5,544		5,544		5,544		5,544	
# Obs.	13,769		13,769		13,769		13,769	

*Asy•Z are calculated using standard errors clustered by individual

Table 2.5: **Main Results**

	Model 1		Model 2		Model 3	
	Coef.	Asy. Z	Coef.	Asy. Z	Coef.	Asy. Z
DTCA Off	**0.025**	**(8.79)**	**0.014**	**(3.60)**	**0.012**	**(3.00)**
DTCA On	**0.017**	**(3.82)**	**0.038**	**(5.01)**	**0.038**	**(4.95)**
Prev. Drug	0.880	(11.50)	4.707	(4.06)	4.688	(3.98)
Price Off	•0.014	•(0.44)	•0.045	•(1.41)	•0.008	•(0.19)
Price On	•0.093	•(6.03)	•0.097	•(6.26)	•0.091	•(5.68)
Health Insurance	0.124	(1.07)	0.099	(0.84)	0.110	(0.94)
Medicaid	•0.015	•(0.33)	•0.030	•(0.64)	•0.045	•(0.94)
Medicare	0.044	(0.97)	0.063	(1.40)	0.073	(1.58)
Family Income (000s)	0.000	(1.34)	0.000	(1.05)	0.000	(0.74)
Education Years	0.008	(1.67)	0.008	(1.71)	0.008	(1.62)
Age	0.154	(16.72)	0.156	(16.74)	0.197	(1.85)
Age^2	•0.001	•(14.91)	•0.001	•(14.95)	•0.001	•(0.64)
CH	2.358	(48.63)	2.362	(48.60)	2.382	(48.35)
HD	0.711	(19.99)	0.725	(20.11)	0.731	(20.05)
DB	0.315	(8.57)	0.313	(8.43)	0.313	(8.34)
HYP	0.312	(10.55)	0.311	(10.45)	0.311	(10.33)
Male	0.101	(3.59)	0.103	(3.62)	0.101	(3.52)
mean(DTCA Exp)					0.014	(0.87)
mean(Age)					•0.040	•(0.38)
mean(Age^2)					•0.001	•(0.85)
mean(Drug Ins)					0.085	(1.66)
mean(Fam. Inc (000s))					0.000	•(0.24)
Mean(Health Insurance)	0.514	(3.70)	0.523	(3.74)	0.473	(3.25)
Initial Condition	2.067	(35.38)	2.052	(35.21)	1.986	(16.29)
Product Dummies	Yes		Yes		Yes	
Season Controls	Yes		Yes		Yes	
Time Controls	Yes		Yes		Yes	
Trends	No		Yes		Yes	
Constant	•11.713	•(30.39)	•11.411	•(15.26)	•10.977	•(14.43)
Random Effect	1.194	(40.27)	1.204	(40.48)	1.219	(40.60)
Likelihood Function	•17,747		•17,659		•17,638	
# Individuals	59,525		59,525		59,525	
# Obs.	208,530		208,530		208,530	

Table 2.6: **Elasticities of Demand for Advertising in Period 1**

Overall Elasticity	Period 1		Period 2		Period 3		Period 4	
Results Based On Model 2 Estimates	Elasticity	s.d.	Elasticity	s.d.	Elasticity	s.d.	Elasticity	s.d.
Overall	0.1071	(0.014)	0.0207	(0.006)	0.0053	(0.003)	0.0018	(0.002)
Population Not On a Drug	0.1588	(0.032)	0.0259	(0.014)	0.0073	(0.007)	0.0027	(0.004)
Population On a Drug	0.0857	(0.016)	0.0180	(0.007)	0.0038	(0.003)	0.0011	(0.002)
Overall By YEAR								
1996	0.0581	(0.045)	0.0306	(0.032)	0.0163	(0.023)	0.0100	(0.018)
1997	0.0815	(0.045)	0.0281	(0.025)	0.0099	(0.013)	0.0046	(0.009)
1998	0.0866	(0.044)	0.0175	(0.021)	0.0029	(0.008)	0.0008	(0.004)
1999	0.0593	(0.034)	0.0107	(0.014)	0.0029	(0.008)	0.0008	(0.004)
2000	0.1089	(0.040)	0.0157	(0.015)	0.0030	(0.007)	0.0006	(0.003)
2001	0.1561	(0.040)	0.0309	(0.018)	0.0083	(0.009)	0.0020	(0.004)
2002	0.1379	(0.030)	0.0215	(0.012)	0.0043	(0.006)	0.0009	(0.003)
Results Based On Model 1 Estimates								
Overall	0.1091	(0.015)	0.0196	(0.007)	0.0044	(0.003)	0.0010	(0.001)
Population Not On a Drug	0.2459	(0.131)	0.0347	(0.040)	0.0080	(0.018)	0.0015	(0.008)
Population On a Drug	0.0387	(0.010)	0.0084	(0.006)	0.0020	(0.003)	0.0005	(0.001)

Table 2.7: **Consumer Heterogeneous Effects**

	(1)		(2)	
	Coef.	Asy. Z	Coef.	Asy. Z
DTCA Off	0.038	(2.70)	0.035	(2.03)
DTCA Off * Med. Ins			•0.017	•(1.21)
DTCA Off * Price Off			•0.004	•(0.63)
DTCA On	0.064	(4.07)	0.085	(3.03)
DTCA On * Med. Ins			•0.050	•(1.84)
DTCA On * Price On			0.001	(0.36)
DTCA * Med. Ins	•0.019	•(1.53)		
DTCA * Price	•0.001	•(0.23)		
DTCA * Age	0.000	(0.56)		
DTCA * CH	•0.009	•(1.84)		
DTCA * Educ. Yrs.	•0.002	•(2.03)		
DTCA * Fam Inc. (000s)	0.000	•(0.13)		
Med. Ins. * Prev. Drug			0.380	(1.10)
Education Years	•0.029	•(0.62)	•0.030	•(0.63)
Medical Insurance	0.062	(1.37)	0.062	(1.38)
Random Effect	1.205	(40.44)	1.203	(40.43)
Likelihood Function	•17,653		•17,656	
# Individuals	59,525		59,525	
# Obs.	208,530		208,530	

Table 2.8: **TV & FDA Rule Change**

	(1)		(2)	
	Coef.	Asy. Z	Coef.	Asy. Z
DTCA Off TV	0.014	(3.15)		
DTCA Off Non•TV	0.015	(1.10)		
DTCA On TV	0.029	(3.09)		
DTC On Non•TV	0.080	(3.06)		
DTCA Off			0.033	(2.29)
DTCA Off *FDA Rule Chg.			•0.017	•(1.33)
DTCA On			0.032	(2.33)
DTCA On *FDA Rule Chg.			0.006	(0.52)
Likelihood Function	•17,657		•17,658	
# Individuals	59,525		59,525	
# Obs.	208,530		208,530	

Table 2.9: **Product Advertisments**

	(1)		(2)	
	Coef.	Asy. Z	Coef.	Asy. Z
DTCA Off	0.014	(3.59)	0.014	(3.60)
DTCA Own	0.030	(2.75)		
DTCA Own *Lipitor			0.011	(0.63)
DTCA Own * Pravachol			0.045	(2.11)
DTCA Own * Zocor			0.041	(2.43)
Other DTCA	0.037	(4.63)	0.034	(4.14)
Likelihood Function	•17,653		•17,652	
# Individuals	59,525		59,525	
# Obs.	208,530		208,530	

Chapter 3

Do Low-Quality Products Affect High-Quality Entry? Multiproduct Firms and Nonstop Entry in Airline Markets

[1]

3.1 Introduction

From breakfast cereals to computers to airline flights there are many differentiated product industries in which firms offer multiple products in the same market. However, there are relatively few empirical papers that examine the entry decision of

[1] I am grateful to Ken Hendricks and Randal Watson. I would also like to thank Shane Carbonneau and Bill Brennan for comments.

multiproduct firms. This paper studies the effect of product ownership and quality on the decision to enter a market in the airline industry. The market considered in this paper is transportation services between two cities. I consider two types of products in the city pair market: nonstop service and one-stop service that stops in a hub before reaching the destination city. This paper empirically examines the decision of an airline to offer high quality nonstop service between cities given that the airline may be offering lower quality one-stop service.

In this paper I consider nonstop and one-stop flights to be vertically differentiated services. The nonstop service is a higher quality than the one-stop service in terms of travel time. Several demand studies show that consumers prefer more direct flights.[2] One-stop services also vary in quality. I proxy for the relative quality of the one-stop service using a measure of the directness of the one-stop flight.

I will use a simple example and the diagram below to illustrate the type of strategic situation analyzed in this paper.

[2] For example, the demand study by Berry et al (1997) finds that passengers prefer direct flights relative to indirect flights. Direct flight includes all nonstop flights and flights in which there is a stop but passengers do not change planes. An indirect flight is a flight in which a passenger changes planes. Borenstein (1989) finds that each on-plane stop implies a discount of 3 percent to 13 percent in price and 3 to 8 percent discount for each plane change made.

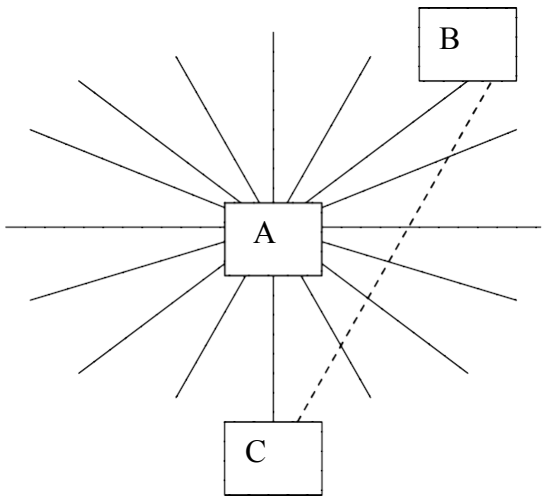

Figure 3.1: Hub Competition

Suppose we have just two airlines, X and Y. Suppose that airline X has a hub at A and offers one-stop service in the B to C market through the hub. Airline Y does not have any service in the market. The entry game considered in this paper is the decision of airline X and airline Y to enter the B to C market with nonstop service. I view the one-stop service as affecting nonstop entry through both cannibalization and business stealing effects. The business stealing effect is the effect that competing rival one-stop services have on the profits from the entering nonstop service. On the other hand, for airlines that own one-stop services, offering nonstop service cannibalizes demand for their existing service. Relative to airlines that have no services in the market, airlines that offer one-stop service have lower incremental profits from offering nonstop service. In the above example, airline Y considers the business stealing effect from competing with the one-stop service in

the market. Airline X considers cannibalization of its own one-stop service that acts as a disincentive for entering the market. One might expect that both cannibalization and business stealing effects to increase as the quality of one-stop service in the market increases. The model in this paper also considers competition between nonstop services. One might expect profits to decrease when rival airlines enter the market with nonstop service.

This paper models nonstop entry of airlines as a noncooperative entry game, which allows for an economic interpretation of the estimated coefficients. The basic empirical approach of this paper closely follows Berry (1992) and uses a simulation estimator to recover the reduced-form incremental profit from offering a nonstop flight. The model differs from previous work in airline entry in two important ways. First, I focus on the nonstop entry decision while most other research aggregates across one-stop and nonstop entry. Reiss and Spiller (1989) find that the type of services in airline markets (i.e. number of firms offering direct flights or indirect flights) is an important determinant of the level of competition in the market, not just the number of airlines in the market. They argue that aggregating across service segments may lead to incorrect inference about the profitability from entering a market. A second important difference from previous empirical work is that I allow the ownership of one-stop service through a hub to affect the incremental profitability of airline entry.

As theory would suggest I find evidence that both cannibalization and business stealing are important in shaping nonstop entry of airlines. I also find that the quality of the one-stop services in the market determines the size of the cannibalization and business stealing effects. Therefore, the ownership structure and quality of the one-stop services can impact the number of nonstop entrants.

Examining the multiproduct entry decision in airline markets has become more relevant as many major network carriers began operating low-cost divisions in

the 1990s.[3] The low-cost divisions of major carriers operating during the period of my sample include Metrojet (US Airways), Delta Express, Continental Express and United Shuttle. The low-cost divisions were started in an attempt by major carriers to cut costs and compete with Southwest and other low-cost carriers. This strategy has been called the "airline-within-an-airline" strategy because the operations of the low-cost divisions differ from those of the rest of the airline. The low-cost divisions cut back on passenger amenities and shifted emphasis from hub-and-spoke to point-to-point route strategies. In many cases this involved carriers expanding nonstop service to markets outside of their hubs. It is often the case that major network carriers offer nonstop service in markets in which it also operates one-stop service through a hub. Some examples of new entry of this type in 2000 include: In the Boston to Myrtle Beach market Delta offered both a nonstop flight and a one-stop flight through Atlanta. In the Las Vegas to Tulsa market Delta offered both nonstop service and one-stop service through Salt Lake City. In the Boston to Raleigh market US Airways offered a nonstop flight and a one-stop flight through Charlotte.

The issues raised in some cases presented to the Department of Justice suggest that this paper may be of interest to policy makers. Several low-cost carriers complained to the Department of Justice because major network carriers began offering competing nonstop service in markets that are also served with one-stop service through a hub. A primary reason for these complaints was that it is relatively unusual for major network carriers to enter these types of markets. In 1995 ValuJet complained when US Airways began offering competing nonstop service from Dulles to Boston and Dulles to Hartford. ValuJet argued that US Airways in the prior 10 years had not operated any service through Dulles that was not a major hub and that entry by US Air was anticompetitive. In 1996 Air South com-

[3] The major network carriers in my sample are American Airlines, Continental, Delta, United Airlines, US Airways, Northwest Airlines and TWA. I refer to these carriers as major "network" carriers to differentiate them from Southwest which is one of the larger carriers, but operates more like a low-cost carrier.

plained that Continental had attempted to overlay its new service in three markets: Charleston-Newark, Columbia-Newark, and Myrtle Beach-Newark. This paper provides some insight into the types of markets in which an airline may choose to offer both one-stop and nonstop flights and why these routes may be offered.

The structure of this paper is as follows: Section 2 discusses some of the related literature in airline entry, Section 3 discusses the development and structure of airline networks, Section 4 discusses the data and variables used in the analysis, Section 5 discusses the econometric model, section 6 discusses the estimates and predictions of the model, and the final section concludes.

3.2 Literature Review

There are many studies that look at entry in the airline industry, but few of them incorporate a structural model of competition. Since many studies have found that competition is an important determinant of entry in airline markets, a structural model of entry should do a better job of predicting the behavior of airlines than a more naive model. In this section I review some of the structural airline entry papers.

Reiss and Spiller (1989) model the competition between differentiated direct and indirect services. Direct service includes all nonstop flights and also includes all flights in which there is no change of planes. Indirect service means a passenger changes planes. They incorporate both entry and price competition in a structural model and examine how direct entry affects price competition in the indirect and direct service market. They find that the indirect service category is significantly more competitive if a direct competitor is also in the market. They also find that within a route there can be large differences in direct and indirect competition. This last point suggests that different service types should not be aggregated, adding support to the approach taken in this paper. There are two key differences between

Reiss and Spiller's work and this paper. First, the Reiss and Spiller paper only examines markets with one or fewer direct entrants, while my paper considers markets in which there may be several airlines offering nonstop flights. Second, Reiss and Spiller assume carriers do not own both a direct and indirect flight in the same market, while this paper is explicitly interested in the effect of owning one-stop service on nonstop entry.

Berry (1992) examines the role of market presence in both endpoint airports and its effect on entry. He aggregates across service types when defining entry, and allows for multiple entrants. He assumes that entry affects the profitability of all airlines symmetrically. This assumption implies that whether Southwest or American Airlines enters a market they have the same effect on the profitability of other airlines in the market such as Delta or Continental. However, Berry's model allows airlines to have both observed and unobserved heterogeneity in fixed costs. He finds that the heterogeneity in airline presence at both endpoint airports is an important determinant of entry. Berry also finds that his structural model of airline competition produces more realistic predictions of airline entry behavior than more simple entry models.

Ciliberto and Tamer (2004) relax the assumption that entry affects the profitability of competing airlines symmetrically. Allowing asymmetric competitive effects between airlines makes the model sufficiently flexible to allow for Southwest to compete differently with American than with Delta. In fact, their model allows for a very general profit function specification so that different carriers may have entirely different profit functions. They find that there is significant heterogeneity in competition between airlines.

Although Ciliberto and Tamer capture an important aspect of airline heterogeneity, similar to Berry they also aggregate across nonstop and one-stop service types. Because they aggregate across service types it is difficult to determine whether

the asymmetry in competition in their model arises because of the different service types being offered by different airlines, or if airlines actually price compete differently with each other. One might expect that large network carriers like Delta and American that enter many markets with one-stop service have less of an impact on the profits of carriers like Southwest that enter many markets with nonstop service. In fact, in one of their specifications they find exactly this result. They find that American and Delta have limited effects on the profits of other carriers relative to Southwest. It is possible that service heterogeneity may be influencing their results. In my paper, I assume that there is symmetry in nonstop competition, but allow for asymmetry in competition between the types of services offered.

The current paper is also related to the entry model of Mazzeo (2002). Mazzeo examines a game of product differentiation and entry in motel markets. His model extends previous entry models by endogenizing product-type decisions (e.g. low-quality motel or high-quality motel). He then measures the effects of competition between the different product types. My paper also allows for different product-types to affect nonstop entry. However, I treat one product type as fixed, the one-stop service, and I examine the entry decision of offering nonstop service. One advantage of treating one-stop service as fixed is that I can examine continuous measures of product quality in the one-stop service affecting nonstop entry, while Mazzeo's model captures discrete differences in product quality. Justification for treating one-stop service as fixed is given in the next section of the paper.

3.3 Hub-and-Spoke System and Airline Networks

Before discussing the full model, it is important to have some understanding of the structure of airline networks. After deregulation of airlines in 1978, airlines quickly shifted to a hub-and-spoke system which remains the predominant structure in the

industry today.[4] A hub-and-spoke system brings passengers from "spoke" cities into a "hub" city where passengers transfer planes and fly to destination "spoke" cities. There are both efficiency and strategic advantages for operating hub-and-spoke networks.

The efficiency of the hub-and-spoke system has been thoroughly studied both empirically and theoretically. The hub-and-spoke system creates high density along spoke routes, which leads to lower costs per passenger. By channelling passengers into a hub, the hub network is able to generate greater density along all the spokes. Therefore, hubs allow for more efficient use of facilities and aircraft. Empirical studies by Caves, Christensen, and Tretheway (1984) and later Brueckner and Spiller (1994) estimate significant cost savings from economies of density, which suggest that this is a key factor motivating the restructuring of the industry following deregulation. Brueckner, Dyer, and Spiller (1992) examine the structure of the hub network directly and show that there is a relationship between higher traffic density across the network and lower fares. Hendricks, Piccione, and Tan (1995) provide a formal theoretical model to explain economies of spoke density, and how hub-and-spoke networks arise from basic assumptions about cost savings from economies of density.

Other reasons airlines form hub-and-spoke networks involve strategic advantages. Hendricks, Piccione, and Tan (1997) explain why it is generally a dominant strategy for hub airlines not to exit a hub-spoke market. They argue that the hub-spoke market produces complementarities in flights that connect in the hub. A monopoly hub that faces competition from a regional carrier along a spoke can credibly remain in the market under price competition because exiting a spoke causes losses in its complementary markets. This credible threat keeps potential entrants out of spoke markets. A hub carrier offering frequent flyer miles also has a strategic

[4] See Graham, Kaplan and Sibley (1983) for a description of key changes after regulation.

advantage. Passengers that use frequent flyer miles value the hub carrier's frequent flyer miles more than other carriers because the hub serves a greater variety of destinations.[5] Hence, passengers that use frequent flyer plans may be more likely to choose the hub carrier. In the remainder of this paper I refer to the combined efficiency and strategic effects of airline networks as network effects.

If the network effects are sufficiently large, then after a hub-and-spoke network is formed hub carriers will not find it profitable exit spoke routes. Therefore, nonstop routes out of a hub are essentially fixed. A fixed hub network implies that one-stop routes made through the hub are also fixed because passengers can typically connect in a hub. An example using the figure 3.1 from the introduction helps to illustrate this point. Suppose there are 17 cities and 16 spoke routes connected directly through hub city A. Assume that all connecting flights through A are offered. Now consider the marginal decision to offer nonstop service between two spoke cities B and C as shown by a dotted line in the above figure. The decision to serve the market between B and C with nonstop service is exogenous to the decision to serve the market B to C through the hub if the entry decision in the A to C and A to B markets is unaffected. Because A is a hub exiting a spoke market A to C or A to B implies exiting 15 connecting markets.

To see that large hub-spoke networks are relatively fixed, I examine the entry and exit rates between all city pairs in a sample of the 50 largest cities. Table 3.1 in the appendix shows the number of nonstop entry and exits from the second quarter of 1996 to the second quarter of 2000. (The construction of the data and the sample will be explained in detail in the next section of the paper.) I find that entry and exit rates are much lower for hub carriers in their hub-and-spoke markets relative to entry and exit rates in markets where no carrier operates a hub.[6] The hub carriers

[5] See Borenstein (1989) for a discussion of frequent flyer marketing strategy and empirical work on the effects of airport dominance.

[6] Exit (Entry) rates are computed as the fraction of carriers observed Entering (Exiting) from 1996 to 2000 out of the total number of nonstop flights in 1996.

at their hub had an exit rate of 1.33 percent in their spoke markets, compared to an exit rate of 19.45 percent in nonhub markets in which no carrier operates a hub. The entry rate in hub markets is also much lower for hub carriers at their hub relative to entry rates in non-hub markets. The entry and exit rates provide strong evidence in support of treating hub markets as fixed.

3.4 Data

The primary data source used is the second quarter data from 2000 of the Official Airline Guide (OAG). The OAG data are a weekly schedule of all nonstop flights operated by domestic and international carriers. Each observation in the database represents a particular flight by a carrier in a quarter and includes information on the identities of the carrier, the origin and destination airports and the days of the week in which the flight operates. The OAG data are used to determine which carriers offer nonstop service.

A secondary source is from the U.S. Department of Transportation's "Origin and Destination" survey. The Origin and Destination survey is a 10 percent random sample of all flight coupons by domestic carriers in the US. The data used are from the second quarter data from 2000 from the Data Bank 1A (DB1A). The DB1A data contains a list of fares and the number of passengers traveling on a route. Route information includes the origin and destination airports, the stops where passengers changed planes, and whether the trip was one-way or round-trip. It also includes the great circle distance of each route. To supplement the information from the above data sets I use 1999 MSA population estimates taken from the U.S. Census Bureau.

I define nonstop service as a carrier offering 52 flights a quarter (approx 4 a week). To check the accuracy of the OAG data, I also require that I observe at least 500 passengers (50 passengers in the 10 percent sample) flying directly between the

origin and destination cities in the DB1A sample.

Using the DB1A data I chose the top 188 cities with the largest number of passenger enplanements in the second quarter of 2000. I then construct a data set that includes all nonstop travel between 188 cities in the second quarter of 2000. I define a city as the MSA. Included in this sample are cities with multiple airports. For example, I count entry in the Portland to Oakland market the same as entry in the Portland to San Francisco market. There is clearly a trade-off between selecting a city pair as the relevant market rather than an airport pair. An argument for using airport pair markets is that business travelers often have a strong preference for flying out of major airports. This is the view taken in Ciliberto and Tamer (2004). However, by looking at the city pair market my estimates capture an important aspect of competition between major network carriers and low-cost carriers operating in secondary airports in the same city. For instance, Southwest operates out of Oakland in the San Fransisco bay area and competes with airlines flying out of the San Fransisco airport. Similarly, both Reiss and Spiller (1989) and Berry (1992) view airline markets as city pairs.

I define an airline as having a hub in a city if the features of the airline network at that city satisfy two selection rules. First, using DB1A data, I select cities in which a single carrier transports more than 300,000 passengers that make a single connection through the hub to one of the 188 selected cities mentioned above. The first rule eliminates all but 20 possible hubs. The second rule requires that 30 or more nonstop routes are offered out of the hub. Applying the second rule leaves 18 selected hubs. These 18 hubs account for 81.4 percent of all one-stop traffic.[7]

To show that these selected hubs vary significantly from other airport operations, I contrast characteristics of the selected hubs with the next 18 potential

[7] I calculate this statistic as (total number of indirect passengers changing plans at the airport)/(tot passengers changing planes at the airport+total passengers originating from the airport+total passengers destined for the airport)

hubs with the highest number of stopping passengers. The next 18 potential hubs account for only 12.5 percent of all one-stop traffic. Another characteristic in which the selected hubs differ from the next 18 is in the percent of the passengers using the hub that are changing planes. The average airport in one of the selected hubs has 44.14 percent of passengers changing planes, while the average airport in the next 18 potential hubs has only 14.6 percent of passengers changing planes. The types of carriers operating in the next 18 potential hubs are also distinct from those in the 18 selected hubs. Nine of the next 18 hubs are operated by Southwest, and four others are operated by other low-cost carriers. The other carriers in the group of the next 18 include United Airlines at San Francisco, Continental at New York , United Airlines at Los Angeles, and United Airlines at Washington DC. See table 3.8 for a detailed list of the selected hubs and the next 18 potential hubs. Table 3.8 also has additional information about the operations at each hub and is sorted by the number of stopping passengers.

The next step in constructing the data is defining one-stop service through a hub. The networks of large airlines allow them to serve the same route in a number of different ways. For purposes of this paper, I am interested in the one-stop route that is the closest substitute with nonstop service. Therefore, I select the most direct route passing through a major hub. I use the nonstop entry information out of hubs and the location of the hubs to select the most direct one-stop flight through the network. To illustrate this construction, consider Continental Airline's Austin to New York market. In the data I observe that there is nonstop service from Continental's hub in Houston to both Austin and New York. Next, I examine whether this is the most direct one-stop flight that Continental offers through a hub. Although they have a hub in Cleveland, the one-stop flight through Houston is more direct. In this example I assume that the relevant service is the one-stop service being offered through the hub in Houston.[8]

[8] I checked this example on Expedia on March 3, 2005, and found that Continental offered both

In defining one-stop service I exclude very low quality one-stop services offered through hubs. I determine criteria for what one-stop service may be considered "low-quality" by looking at the directness of one-stop flights that people typically fly as observed in the DB1A data. Typically I did not observe one-stop passengers on routes in which the distance is more than twice the distance as the crow flies between two cities. Therefore, I do not consider an airline as offering one-stop service if the distance along the two segments of the one-stop service is more than twice twice the direct distance between the city pair.

In selecting the subsample of city pair markets, I begin by following Berry (1992) by choosing all city pair combinations between the 50 most populated cities. The highest populated cities are used because these are most likely to have nonstop entry. An additional reason for using the 50 most populated cities is that the assumption of hub networks being fixed is more plausible in larger markets where the number of passengers in the network would diminish by a great amount if the market is exited.[9] I then eliminate city pair markets based on two criteria. First, markets in which any carrier operates a major hub are eliminated. As argued before, because of the strong complementarities in hub markets, I treat nonstop entry out of hubs as fixed. It would be logically inconsistent to model the entry decision by hub carriers at their hubs while treating it as fixed in other markets. The second type of market that is eliminated are city pair markets for which the distance between the cities is less than 300 miles. These markets are eliminated because I want to focus on markets where nonstop and one-stop services are likely to compete. In short distance routes the closest substitute to nonstop entry may be car travel and not a one-stop flight. After applying these criteria I am left with 511 city pair markets.

nonstop and one-stop service between Austin and New York where the one-stop service is offered through Houston. In constructing the one-stop routes, I do not use information on where passengers are observed traveling. The problem with using the observed routes taken by passengers is that it depends on the quality of the other services in the market and the pricing decision after entry.

[9] Recall that the entry and exit statistics used for arguing that hub networks are fixed were based on the 50 largest cities.

3.4.1 Variables

The variables used in this paper include market variables and airline specific variables. The market variables include both population and distance variables. The population variable is constructed from the 1999 U.S. Census Data measured as the geometric mean of the population in the two cities in millions.[10] The distance variable is the great circle distance between the two cities in hundreds of miles.[11]

The airline specific variables capture the network effects of an airline and the characteristics of the one-stop services in the market. Although the larger hubs are removed from the sample, the network effects that are present in the remaining cities are still important determinants of entry. For example, Southwest has no major hubs, but it has a significant presence in a number of cities. To capture network effects I use the variable NetworkEjject which is the number of markets entered nonstop out of the two endpoint cities to the 188 cities in the large sample, but excluding the nonstop route on the city being considered. For, consider calculating the network variable for airline X deciding whether to enter the A to B market. First, I exclude the A to B entry and then look at the number of routes airline X has out of each city. Suppose they have 4 nonstop routes out of A and 5 nonstop routes out of B then the NetworkEjject variable is 4 + 5 9.

The variable top is a dummy variable which is one if an airline offers a one-stop service through a hub and is equal to zero otherwise. This variable captures the cannibalization of an airlines existing service. The effect of this variable on the non-stop entry of a firm is expected to be negative. The variable OneOth top equals one if there is another airline in the market offering one-stop service. The variable NumOth top equals the number of rival airlines offering one-stop service

[10] In the A to B city pair market the population variable is Pop = (PopulationinCityA/1million) * (PopulationinCityB/1million). A similar measure is used by Berry (1992)

[11] In the case where there are multiple airports in a city, I take the average distance between airports in the city.

in the market.

I measure quality of the one-stop service as the total distance flown on the one-stop flight minus the great circle distance or distance as the crow flies between the two cities. For instance, the quality of the one-stop flight in the Austin to Portland market with a stop in Houston may be calculated taking the following steps: calculate the distance from Austin to Houston, add the distance from Houston to Portland, and then subtract the distance crow flying distance between Portland and Austin. I call this variable CircDist. A similar measure is used by Reiss and Spiller (1989) and Borenstein (1989).[12] As this variable increases the quality of the one-stop service is lower. The variable OwnCircDist is the quality variable of an airline's own one-stop service in the market. If an airline does not have a one-stop product in the market then OwnCircDist equals zero. The variable RivalCircDist is the quality of the highest quality rival airline in the market. If no airline is in the market then RivalCircDist equals zero.

The model in this paper estimates a game of competition between entrants. I consider an airline as a potential entrant in this model if the airline has some presence in both cities of the city pair market in the second quarter of 2000.[13] This definition may be justified if one views nonstop entry as actually occurring in two stages: first airlines decide which cities they will enter, and second they decide which routes will be entered nonstop out of the city. The game analyzed in this paper takes the first stage of entry into a city as given and then analyzes the decision to enter nonstop in a particular city pair market. The reasons for using this definition of entry is that it focuses the entry game on the most likely set of entrants. This definition of a potential entrant differs from that used in Berry (1992) which defines

[12] [2] One could argue that a more accurate measure of quality may be total time of a flight or some on-time performance measure at a hub. Although these measures may be a more accurate reflection of consumer preferences, it is not clear that these measure of quality are exogenous to competition. Mazzeo (2003) finds that the on-time performance of a carrier improves with increased competition in the market suggesting that on-time performance may be chosen by carriers.

[13] [3] By "presence" I mean that there is are some passengers observed flying in or out of the city.

an airline as a potential entrant if they have some presence at either endpoint city. I find that this definition includes many firms as potential entrants that are not likely to enter.

3.4.2 Descriptive statistics

Before describing the full empirical model, I examine some descriptive tables that provide some insights into the determinants of nonstop entry. Table 3.2 tabulates descriptive statistics by the number of airlines offering nonstop service. The first column lists possible number of nonstop entrants and the second column shows the frequency in which that number of nonstop entrants are observed in the data. The frequencies show that in most of the markets in the sample there is no airline offering nonstop service. The third through sixth columns show the mean of the population variables, distance, number of one-stop services and the most direct one-stop service in the market. I find that distance is typically greater in markets in which no carrier offers nonstop service. This may reflect the success of low-cost carriers in entering short distance nonstop routes, as well as the efficiency of hubs in traveling longer distances. The table also shows that nonstop services increase with the population. In a markets with fewer nonstop entrants the highest quality one-stop service is greater.

Table 3.3 shows the number of markets entered by each airline and the average network effect for each airline. There are two points to note in this table. First, Southwest enters more markets than any other airline in the sample. This is not surprising given Southwest's strategy of avoiding direct competition with major hubs and their focus on entering markets with nonstop (i.e. point-to-point) service. Second, there is a strong association between the network effect variable and the number of markets a carrier enters with nonstop service.

Table 3.4 shows some basic statistics of the CircDist quality measure. The

quality measure is listed in order of quality in the market. Note that the average circular distance of the most direct one-stop flight in the market is about 25 miles. This suggests that for most cities there is a major hub that offers fairly direct service. This may reflects the strategic placement of hubs in central locations in the country that can offer more direct service to more destinations. The average CircDist for the second highest quality firm is more than three times greater than the highest quality.

3.5 Econometric Model of Entry

I model airlines as playing a complete information entry game. At the beginning of the game, each potential entrant knows its own and its rivals' post-entry incremental profits. Incremental profits for offering nonstop service depend on existing one-stop services in the market through a hub, network features in the city pair, observed and unobserved demand and cost factors, and the number of rivals entering with a nonstop service. Given this information, airlines enter the market if their incremental profits are positive, otherwise they do not enter. The econometric entry model in this paper is very similar to Berry (1992). The primary differences are that I focus on the nonstop entry and incorporate information on one-stop services.

I assume the following functional form for incremental profits:

$$\pi_{ik}(N_i) = x_i \underset{Market}{\beta} + x_{ik} \underset{Network}{\beta} + x_{ik} \underset{OneStop}{\beta} - bN_i + aE_i + \omega^* \sqrt{1 - a^2}\, E_{ik} \tag{3.1}$$

The variables x_i are market specific variables capturing observed market specific demand and cost factors. The variables $x_{ik}^{Network}$ capture the network effects of firm k in market i. The variables $x_{ik}^{OneStop}$ capture the influence of airline k's own one-stop service and the one-stop services of its rivals. I also allow for both market and firm specific portions of unobserved profits E_i and E_{ik}. The parameters to be

estimated are $\beta_{Market}, \beta_{Network}, \beta_{OneStop}$ and a. The variable N_i is the number of airlines that enter in the city pair market, and is the dependent variable in the above model. I assume that additional entry causes profit loss to other airlines in the market so b □ 0.[14]

The number of airlines that enter in a pure strategy Nash equilibrium equals the maximum number of airlines that can profitably enter a market. Formally, the equilibrium number of airlines that enter in market i is:

$$N_i^* \quad \max_{0<n<K_i} \{n : w_{ik}^*(n) > 0\} \tag{3.2}$$

where K_i is the number of potential entrants in market i. The number of airlines that enter in equilibrium is unique. To see this, suppose it is not unique, then there is an equilibrium number of airlines $N_i \quad N_i^*$. If $N_i > N_i^*$ this implies that some airline must be making negative profits, and if $N_i < N_i^*$ then there exists a airline that could profitably enter the market but chooses not to enter.[15]

The identity of entering airlines in an equilibrium of the above game is not unique. Consider the simple example of a market with two potential entrants that each find it profitable to enter as a monopolist, $w_{ik}^*(1) > 0$, but do not find it profitable to enter in a duopoly market $w_{ik}^*(2) < 0$. The above model implies that $N_i^* \quad 1$, but it is unclear which of the two airlines enters.

To use information on the identity of airlines I follow Berry by assuming that airlines enter in the order of post entry profitability. He justifies this selection by assuming that airlines are playing a post-entry war of attrition that would instantly eliminate less profitable airlines if more than N_i^* enter as in Judd (1985). Under the "most-profitable firm enters first" selection rule, let i_{ik}^* be an indicator of entry by airline k in market i. The function i_{ik}^* is 1 if firm k in market i is one of the N_i^*

[14] [4] More flexible specifications of the above model suggested that the number of airlines that enter the market affects profits linearly.

[15] [5] This follows directly from Berry (1992)

most profitable airlines in the market, and 0 otherwise.

3.5.1 Method of Simulated Moments Estimator

I estimate the above profit function using a Method of Simulated Moments (MSM) estimator (See McFadden (1989) and Pakes and Pollard (1989)).[16] I estimate the model using a frequency simulator. I start by taking R simulation draws. For a given set of parameter values b and simulation draw r E (1...R) I evaluate the profit function for all potential airlines in the market and I solve for the Nash equilibrium number of firms in each market $N_{ir}(b)$. I also use the ordering assumption to determine the identities of the $N_{ir}(b)$ firms in the market, where the entry prediction for market i for airline k and simulation draw r is $i_{ikr}(b)$.

An unbiased estimator of the number of airlines that enter market i is found by averaging over the predictions for each simulation draw. That is, the predicted number of airlines entering in market i is $\hat{N}_i(b) \quad \frac{1}{R}\sum_{r=1}^{R} N_{ir}(b)$. To obtain an unbiased estimator of the entry of individual airlines, I average over the individual entry predictions for each carrier. The unbiased prediction of entering for airline k in market i is $\hat{i}_{ik}(b) \quad \frac{1}{R}\sum_{r=1}^{R} i_{ikr}(b)$.

Let the observed number of airlines entering in market i be N_i^*, and let the observed entry decision of airline k in market i be i_{ik}^*. I specify the prediction error in the number of airlines for market i as $u_i(b) \quad N^*_i - \hat{N}_i(b)$. I specify the prediction error in the identity of airline k in market i as $u_{ik}(b) \quad i^*_J - \hat{i}_i(b)$. The number of potential entrants varies in each market. To keep the number of moment conditions the same across markets, I choose the two potential entrants in the market with the highest network effect variable. The vector of prediction errors is then $v_i(b) \quad u_i, u_{il}, u_{i2}$.

From these predictions errors I construct moments. Let $j(Z_i, Z_{il}, Z_{i2})$ be an

[16] This section closely follows Berry (1992).

L dimensional function of market i's exogenous data Z_i and the exogenous data for airline k be Z_{ik}. Then given M markets and that $v_i(b)$ is uncorrelated with $j(Z_i, Z_{i1}, Z_{i2})$ implies

$$g(b) \frac{1}{M} \sum_i v_i(b) \quad j(Z_i, Z_{i1}, Z_{i2}) \quad \frac{1}{M} \sum_i g_i(b)$$

The value g(b) is a vector of size L and the true b satisfies E[g(b)] 0. The MSM-estimator $\hat{b}$ is defined as the minimizer of weighted distance between observed and simulated moments, such that, $\hat{b}$ solves

$$\arg \min_b g^t(b) n g(b)$$

where the n is a weight matrix. I estimate this model in two stages. In the first stage I set n equal to the identity matrix to get a consistent estimate of b. In the second stage I calculate the optimal weight matrix n E (g(b) g^t(b)) by using estimates of b from the first stage and solve the above equation again to obtain my final estimates. I use simulated annealing to solve for the minimum of the objective function.

I employ different instruments depending on the specification of the model. The instruments used are discussed along with the each specification in the next section. The standard errors are computed using the formula in Pakes and Pollard (1989) where the asymptotic distribution of $\sqrt{M}(\hat{b} - b)$ is $(1 + \frac{1}{R}) E(\frac{Bg}{Bb}) n E(\frac{Bg}{Bb})^{-1}$.

3.6 Estimates

Before estimating the full model, it may be useful to analyze a simpler probit model that excludes competition from the analysis. Although the simple model excludes competition, it provides a basic approach to look at the impact of one-stop services

on nonstop entry. In addition, if competition with other nonstop entrants is not an important determinant of entry, then a simple probit model will accurately capture an airlines decision to enter a market. Table 3.5 shows two simple probit estimates of entry for all potential entrants in each market. Model 1 only includes an airline's own one-stop service, while model 2 includes features of both an airline's own one-stop service and the service of its rivals. Focusing on model 2, the probit estimate shows that ownership of a one-stop service reduces the probability of entry. This reflects cannibalization of an airline's own service. An increase in the circular distance of an airline's own one stop service increases the probability of entry. A reason for this is that cannibalization effects are reduced as the quality of one's own service are lower. If there is a one-stop rival in the market then the probability of entry declines which is consistent with the existence of business stealing effects. An increase in the circular distance of a rival airline's service increases the probability of entry suggesting that business stealing effects are less for lower quality one-stop service. For each additional one-stop entrant the probability of entering increases. This last result is not consistent with the view that competition is greater as the number of one-stop entrants increases. Although the probit captures many of the effects of interest, it is difficult to know how important nonstop competition is between carriers until looking at estimates from the full model.

Now I look at three specifications of the structural model that incorporates competition with other nonstop entrants. These estimates are shown in table 3.6. The first model is a benchmark model that excludes information on one-stop service in the market. The model is similar to that in Berry (1992), but applied to nonstop entry. In this benchmark model there are 19 moment conditions.[17] Most of the

[17] [7] The instruments Z_i for the market specific error term u_i include the exogenous covariates of population and distance. It also includes a count of the number of potential entrants, the number of
firms with the network effect variable greater than 5, the number of firms with the network variable greater than 10, and the sum of the squared share of nonstop services offered out of the city. The instruments for the firm specific error terms u_{i1}, and u_{i2} include all the covariates for the individual firm. In addition, I also use the number of firms in the market with network variable greater than

results of the benchmark model follow expectations. The larger the population in the cities the more likely airlines are to enter because of the greater demand in the market. The longer the distance, the less likely they are to enter because longer distance flights are more often served with one-stop service. The greater the network effect the more likely airlines are to enter. There are two results that are surprising in these estimates. First, the variable on number of rival nonstop entrants in the market is statistically insignificant. This is unexpected given that the structural studies by Berry (1992) and Ciliberto and Tamer (2004) that find competition has high statistical significance. The second surprising result is that the market specific unobservable is insignificant. It is possible that this insignificance may be caused by including the network variable that may capture much of the market specific unobservable profits.

The second specification adds to the benchmark model by incorporating each airlines' own one-stop entry and the circular distance of the service. In estimating this model I include 8 additional moment restrictions to identify the additional parameters.[18] These estimates show that owning a one-stop service of high quality reduces the profits from offering nonstop service. The estimates also show that as the circular distance of an airline's own one-stop service increases, incremental profits from entering also increase. Both of these results are consistent with airlines reacting to cannibalization effects. The result contrasts with the benchmark model because it shows that competition with other nonstop services has a significant and negative effect on profits. These estimates imply that capturing the heterogeneity of airline service ownership in the market may be important for accurately capturing nonstop competition between airlines. In other words, it seems that the benchmark model

10 and the number of potential entrants as additional instruments.

[18] The additional market specific instruments include a dummy of whether there is at least one one-stop service in the market, the total number of one-stop services, and the circular distances of the two most direct one-stop services in the market. Airline specific moment restrictions include the two additional explanatory variables added to the model.

may suffer from omitted variable bias. The magnitudes of the estimated coefficients imply that owning a high quality one stop product with an $OwnCircDist_{ik}$ variable near zero is similar in magnitude to having an additional nonstop rival in the market. This suggests that the magnitude of the cannibalization effects are large in relative terms.

The "full model" includes both an airline's own one-stop service and the one-stop service of rival airlines. The results of this full model are qualitatively similar to the results of the second probit model and the second structural model. The results are consistent with one's own product having cannibalization effects and the rival one-stop and nonstop products having a business stealing effects.

The business stealing effects from rival one-stop entrants are slightly different than those of the probit model. In particular, the coefficient on the number of one-stop entrants variable NumOthOne – top was significant in the probit model, but is insignificant in this specification. However, the coefficient still has an unexpected positive sign. There are a number of potential explanations for this unexpected sign. First, this variable may be correlated with unobserved demand factors such as tourism or business travel in the city pair market. A second explanation is that it may be caused because the model treats one-stop service as a fixed portion of an airlines profits, when in fact the one stop market can affect the variable profits of firms. The unexpected sign could occur in the following setting: Suppose that an airline offers one-stop service in a market and faces competition with other airlines offering one-stop service. The greater the competition in the one-stop service market the less profitability in that market which ultimately reduces the cannibalization effects from offering differentiated nonstop service. Further analysis is necessary to determine which factors are driving this unexpected result.

3.6.1 Predictions and Analysis

This section compares the predictions made by the models estimated in this paper. I compare the full model to the second probit model to evaluate the importance of structurally modeling competition. I also compare the full model to the baseline structural model to check the importance of incorporating information on one-stop service. In this section I find that the simple probit model provides the best fit of the data, but for predictive purposes, the full model produces more reasonable results.

Table 3.7 shows the prediction for each of the three models. The simple probit model seems to perform better than the other two models in terms of within sample prediction. In the sample I observe that the total number of airlines entering the market is 380. The simple probit model predicts that 371.7 airlines enter, the benchmark structural model predicts 355.9, and the full model predicts 358. In terms of mean squared error in predicting the number or the identities of airlines, the simple probit also performs the best, followed by the full model, and in all cases the benchmark structural model performs the worst. The poor performance of the benchmark structural model suggests that incorporating information on one-stop services is important. A potential reason for the predictive accuracy of the probit model is that in many markets in the sample competition between nonstop competitors is not present so the probit model should perform well

In table 3.7 I look at 5 different types of changes in exogenous variables. An increase in the network variable of each potential entrant by 10, more than doubles the number of predicted entrants in the probit model to 824.8, but increases the full model to only 632.6. The reason for this high prediction in the probit model is that it does not account for the increased competition in the market as more airlines enter.

Next I examine the effect of changing circular distance in the market. In

experiment 4 I hold constant the rival services, and I increase each airlines own circular distance by 200 miles. In both the probit and the full model there is only a slight increase in the number of entering firms. In experiment 5 I hold constant each firms own circular distance and increase the rival circular distance by 200 miles. This increases the number of predicted firms entering to 434.1 in the full model, while the probit model predicts 558.2 airlines entering. Again, the reason for the difference in predictions is that the probit model does not account for competition in the market.

In the final experiment I evaluate the total effect of cannibalization from one-stop services by holding constant the rival services in the market and examine the effect on entry if no firm owned a one-stop service (i.e. assuming that One-Stop=0 and OwnCircDist=0). With the full model I find evidence that when cannibalization effects are removed the average number of one-stop services in the market increases to 417.2. For this last experiment it is difficult to make sense of the probit result predicting a decline in entry which is unexpected. Overall the results from this section suggest that the probit estimates are unreliable for making out-of-sample predictions.

3.7 Conclusion and Proposal for Future Research

Empirical studies of entry have largely ignored the role of product ownership in shaping firm entry. This paper explicitly looks at the role of product ownership and its affect on entry decisions in the airline industry. I find evidence that cannibalization of an airline's own one-stop service reduces the probability that an airline enters a market. As the quality of an airline's own one-stop service is lower, the cannibalization effect diminishes. Competition with rival one-stop services is also an important determinant of nonstop entry. A rival one-stop service in the market has a business stealing effect on nonstop entrants. In addition, higher quality one-stop services have a larger business stealing effects than lower quality one-stop

services. Finally, my model predicts that incremental profits from offering nonstop service decline as the number of nonstop rivals in the market increase.

There are a number of potential extensions to this paper. One limitation of the econometric model is that it assumes that the effect of one-stop service enters into the fixed portion of an airlines incremental profit function. This assumption simplified the model by ensuring a unique equilibrium to the entry game. This is a strong assumption given that competition across services may affect one-stop variable profits which could potentially lead to interesting strategic reactions. For example, the reaction of an airline offering one-stop service in a market to a rival entering with nonstop service may actually have two effects. One effect is that the additional competition from a nonstop entrant reduces the profitability for the airline entering with nonstop service. However, a second effect is that competition from the rival reduces variable profits on the one-stop route which, in turn, reduces the cannibalization effect. The entry decision of an airline in this setting will be determined by which of these effects dominates. In future analysis it may be interesting to allow for the one-stop service to enter the variable profit function of the firm. Another important extension is to structurally identify marginal cost, fixed cost and demand factors affecting entry. These components of a firms profit function may be identified using additional information on prices and quantity (i.e.passenger travel).

3.8 Tables

Table 3.1: **Market Entry and Exit Rates**

	Tot. # Mkts. Served in 1996	# Entered	**Entry Rate**	# Exited	**Exit Rate**
Non hub markets	293	144	49.15%	57	19.45%
Hub Carriers at their hub	601	36	5.99%	8	1.33%

Notes:
Sample includes all city pair combinations between the largest 50 U.S. cities with distances over 300 miles
Excludes airlines that stopped operating over this time period
Tot. Nonstop in 2000 in Non hub markets: 380
Tot. Nonstop in 2000 by hub carrier at their hub: 629

Table 3.2: **Summary Statistics**

# of Nonstop	Frequency	Distance (100s of miles)	Pop.	Number of One stops	Quality One Stop (in Miles)
0	319	13.78	1.71	5.69	17.97
1	92	11.02	2.27	5.82	32.18
2	52	11.40	3.16	5.62	35.19
3	29	11.43	3.84	5.66	41.48
4	8	8.95	4.64	3.38	130.43
5	7	13.38	8.37	4.71	17.40
6	1	10.35	4.60	7.00	10.00
8	3	10.17	7.00	7.00	8.33

Table 3.3: **Airline Entry and Network Effects**

Carrier	# Mkts entered	# Mkts Potential Entrant	avg. network effect
American Airlines	45	511	11.22
Continental	23	511	8.09
Delta	44	511	13.79
Northwest	0	511	4.66
United Airlines	37	511	9.83
TWA	9	426	3.60
US Airways	44	359	16.12
Southwest	95	301	23.34
America West	20	213	6.85
Midwest Express Airline	20	170	5.75
Midway Airlines Inc.	14	109	3.66
Alaska	11	70	6.01
Sun Country Airlines	3	70	1.47
American Trans Air	5	69	3.03
Frontier Airlines	0	49	1.63
Airtran/Frontier	0	43	2.84
National Airlines	3	9	1.67
Spirit Air Lines	4	9	3.44
Pro Air Services	0	9	2.00
Jet Blue	3	6	0.67
Legend	0	2	0.00
Vanguard	0	1	6.00

Table 3.4: **One Stop Circular Distance**

Quality Rank High to Low	Mean	Median	s.d.	Min	Max
1st	24.96	6	59.91	0	610
2nd	85.48	43.00	107.00	0	582
3rd	145.14	80.00	157.37	0	932
4th	203.09	161.50	172.67	1	775
5th	297.44	252.00	226.96	4	1047

Table 3.5: **Probit Estimates***

Variables	Model 1	Model 2
Constant	2.163	1.709
	(24.25)	(10.52)
distance (100's miles)	0.048	0.061
	(7.63)	(7.14)
Population	0.117	0.101
	(7.40)	(6.19)
One stop	0.619	0.561
	(6.58)	(5.84)
Own Circ Dist (100s miles)	0.050	0.054
	(2.23)	(2.38)
Rival Circ Dist (100s miles)		0.236
		(5.03)
Rival One Stop		1.274
		(5.43)
Num Oth One Stop		0.156
		(4.69)
Network Effects	0.088	0.088
	(26.02)	(25.52)
log likelihood	667.486	648.233

* Asy Z statistics in parenthasis

Table 3.6: **Main Results***

Variable	Model 1	Model 2	Full Model
Constant	2.483	2.281	1.625
	(30.80)	(24.57)	(5.78)
distance (100's miles)	0.104	0.114	0.128
	(6.80)	(7.66)	(7.42)
Population	0.261	0.408	0.415
	(3.41)	(3.78)	(3.88)
One stop		0.694	0.647
		(4.06)	(4.58)
Own Circ Dist (100s miles)		0.090	0.080
		(2.13)	(1.93)
Rival Circ Dist (100s miles)			0.178
			(2.72)
Rival One Stop			0.829
			(2.49)
Num Oth One Stop			0.070
			(1.55)
Network Effects	0.107	0.102	0.103
	(18.15)	(15.20)	(16.71)
Number nonstop rivals	0.195	0.437	0.522
	(1.33)	(3.23)	(3.27)
Market Correlation	0.077	0.050	0.010
	(.34)	(0.18)	(0.12)
# Observations	511	511	511
Simulation Draws	12	12	12

* Asy Z statistics in parenthasis

Table 3.7: **Predictions and Analysis**

Actual # of Entrants =380

	Probit Model 2	Baseline Model	Full Model
Predicted # of Entrants:			
	371.7	355.9	358.0
Mean Squared Error:			
# of Firms Prediction	0.416	0.502	0.486
Individual Firm Prediction	0.0432	0.0452	0.0441
Entry Impact Analysis:			
1. Change in Pop. (Pop+1)	407.9	427.2	453.0
2. Change in Network +10	824.8	741.4	632.6
3. 200m Increase in Own Circ Di	389.9		374.6
4. 200m Increase in Rival Circ Di	558.2		434.1
5. No firm owns one stop product	356.6		417.2

Table 3.8: **Selected & Potential Hubs**

Selected Hubs

	City	# Nonstop Routes out of Airport	Tot. Passengers Originating or Destined for Airport	Tot. # of Stopping Passengers	% of Passengers changing planes
Delta	Atlanta	104	4,015,240	3,986,290	49.8%
American Airlines	Dallas	92	2,604,720	2,007,650	43.5%
TWA	St.Louis	71	1,245,540	1,867,920	60.0%
US Airways	Charlotte	66	881,050	1,597,110	64.4%
Delta	Cincinnati	92	871,010	1,594,810	64.7%
United Airlines	Chicago	79	2,802,650	1,333,870	32.2%
United Airlines	Denver	62	1,882,570	1,327,200	41.3%
Continental	Houston	84	1,622,740	1,255,920	43.6%
US Airways	Pitsburgh	71	1,025,440	1,179,500	53.5%
Northwest Airlines	Detroit	80	2,040,140	1,147,380	36.0%
America West	Phoenix	42	1,263,610	1,092,680	46.4%
Northwest Airlines	Minneapolis	76	1,952,670	1,078,920	35.6%
American Airlines	Chicago	73	2,009,650	923,320	31.5%
US Airways	Philadelphia	62	1,560,850	648,910	29.4%
Delta	Dallas	45	838,950	571,820	40.5%
Delta	Salt Lake City	37	970,060	563,320	36.7%
Northwest Airlines	Memphis	46	406,510	555,560	57.7%
Continental	Cleveland	65	891,190	340,240	27.6%

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Airtran	Atlanta	26	964,690	363,900	27.4%
Southwest	Phoenix	30	1,566,270	308,430	16.5%
US Airways	Washington DC	46	2,531,650	243,870	8.8%
Southwest	Houston	22	1,234,640	229,580	15.7%
United Airlines	San Fransisco	28	2,745,580	225,570	7.6%
Continental	New York	61	2,613,140	222,670	7.9%
United Airlines	Los Angeles	26	2,386,720	220,030	8.4%
Midway Airlines	Raleigh	20	365,320	197,270	35.1%
United Airlines	Washington DC	25	1,322,200	194,380	12.8%
Southwest	Las Vegas	35	1,987,470	179,770	8.3%
Southwest	Nashville	26	675,240	173,760	20.5%
Southwest	Washington DC	24	1,195,510	166,900	12.3%
Southwest	Dallas	12	1,240,750	166,070	11.8%
Southwest	Chicago	25	1,230,330	162,730	11.7%
America West	Las Vegas	31	968,950	148,750	13.3%
American Trans Air	Chicago	21	790,170	120,370	13.2%
Southwest	Kansas City	22	586,770	116,470	16.6%
Southwest	St. Louis	21	607,650	113,480	15.7%

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